A STUDY OF CONTAGION IN GLOBAL AND LOCAL BANKING INDUSTRIES

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Dedication

To my loving wife

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I would like to express my gigantic gratefulness to my supervisors Professor Kevin Daly, Dr Anil Mishra and Late Dr Salim Akhtar. Words cannot express the effort and training they have given to me. Additionally, I would also like to thank the following individuals for their help and support throughout the entire procedure: My wife for all the support throughout this tuff time, my parents, my sister, my in laws and my friends.

Statement of Originality

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text and where due reference is made. I hereby declare that I have not submitted this material, either in whole or in parts, for a degree at this or any other institution.

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Abstract

This thesis investigates contagion risk for the global and local banking environment using three different distance to risk measures (distance to default - DD, distance to capital – DC and distance to inefficiency- DI). In order to achieve this goal, the research has been divided into three parts (each will have its own chapter) to study the contagion effect in the global and local market. In the first part (chapter 4), the thesis investigates the contagion effect among the top 20 countries of the world. The sample consists of 91 banks from 20 countries across the globe including all G8 and BRICS countries. A list of all these countries and their corresponding banks is included later. The sample also includes all the G-SIB (Global systematically important banks) banks excluding Group BPCE of France (given that Group BPCE originated in year 2009 by merging Caisse nationale des caisses d'épargne and Banque fédérale des banques populaires). In the second part (chapter 5), the thesis examines the local contagion by studying the spill over among top 15 US states. The sample consist of four of the largest banks from each of the sample 15 US state. A list of these banks is attached in the sample description. In chapter 6, the thesis performs a spill over analysis using DD, DI and DC. In order to do so, the thesis has measured the systemic risk using distance to default, distance to inefficiency and distance to capital, which are introduced by the option pricing theory (Merton, 1976). These distance to risk methods are defined as the theoretical difference between the entity's current and breakeven risk position (Distance to default is the difference between the current and default position; Distance to inefficiency is the difference between the current

and inefficient position and distance to capital is the difference between the current and default capital threshold position). Any position lower then this distance to risk measures is considered undesirable for the entity. The study has calculated 2606 daily observations for each of the different distance to risk measures for each bank in the sample for approximately 10 financial years from 2006 to 2015. Then the thesis compute the probability of experiencing extreme shocks in these distance measures of contagion risk using extreme value threshold. This research categorizes these extreme shocks into sub groups for the first two parts and keep the extreme shock unchanged for the last part and examine the contagion risk ascending from the movement of these extreme systemic shocks all through the US and global baking environment using multinomial logistic regression model (MLM). Finally, in chapter 7, the thesis discussed a possible risk management framework based on findings of the previous chapters. It has taken all the banks and divided them into 4 tiers based on their spill over impact. The study suggests that any bank in the 1st tier of the short term or long-term contagion capacity table should be referred to a high degree of regulatory control to enforce not only better capital governance or liquidity requirement but to also enforce overall financial governance as they have a huge impact on the other financial institutions. For the banks in the second and third tier, the authority may adopt a more gradually enforceable governance control in lieu with the current practice and the last tier can do their business in the current regulation, as they pose no real threat to the other peers. At the end, the study also suggests a new generic risk management framework for financial institutions.

List of Peer Reviewed Conferences where paper have been submitted from this thesis

- Choudhury, T. T., et al. (2017). Contagion Risk in Global Banking Sector. 2017 Society for the Advancement of Behavioural Economics Conference. Newcastle University, Sydney, Australia.
- Choudhury, T. T., et al. (2017). Contagion Risk in Global Banking Sector. IFABS Asia 2017 Ningbo China Conference. University of Nottingham Ningbo China & New York University (NYU) Shanghai, China, International Finance and Banking Society.

List of papers under review, submitted or preparing for submission from this thesis

- Contagion risk in global Banking Sector" under "Decision in process" at Journal of Banking and Finance (A*).
- "Contagion risk in US Banking" under review at International Review of Financial Analysis (A).
- "Interbank contagion in US" is being prepared for Pacific-Basin Finance Journal (A).

Chapter 1. Introduction

1.1 Introduction

Financial contagion refers to a “value shock” spreading mechanism whereby the operational difficulties of one financial institution (due to decline in market value) spread to other financial institutions in the system and eventually lead to total economic meltdown. These spillovers within the system can spread from native banks to foreign banks or vice versa (V. Acharya, Drechsler, & Schnabl, 2014). Globalisation suggests that all financial institutions in the world are now linked with each other, even though they operate in different parts of the world (Ghosh, 2016). The global financial crisis (GFC) is the best example of contagion risk in current times (Aloui, Aïssa, & Nguyen, 2011). The impact of this crisis went so deep that not only did it affect the financial and banking system of developed countries (Reinhart & Rogoff, 2014), it also pushed back the economic development of developing and underdeveloped economies (Berkmen, Gelos, Rennhack, & Walsh, 2012). Thus, the contagious nature of risks to the global banking system highlights a serious concern about the future financial stability of the world (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015; Elliott, Golub, & Jackson, 2014; Rogers & Veraart, 2013). The research question of this thesis is to find out and measure the magnitude of contagion risk in the global and local financial system to prevent any future large-scale financial meltdown.

In order to pursue this avenue of research, it is important to measure the spillover effects of contagion between the systematically important banks operating in various geographic locations. This investigation will open up new avenues to protect the global and local economies from systemic contagion risks.

Understanding how and where these shocks are transmitted throughout “the global and local banking system” can also help the policy makers better equip themselves for these unwanted scenarios. The findings of this thesis can help future micro- and macro-level risk management practices involving reliance on long-term wholesale or operational banking transformations that aim to minimise the risk in the cross-border financial activities at a global or local level.

1.2 Conceptual Framework

The built-in risk related to the contagious nature of modern day finance is long established and well researched by previous academics (Feldkircher, 2014; Kenourgios & Dimitriou, 2015; Longin & Solnik, 2001). There are number of studies that examine contagion risk in the financial sector (Carlson & Wheelock, 2016b; Hasman, 2013; Ladley, 2013; Tonzer, 2015). These studies investigate various issues in the contagion risk domain in an attempt to understand the links between financial institutions and to predict contagion across financial systems. Unfortunately these avenue of research is typically difficult for the researchers given the nature of jurisdictional domain differs from global to local context (J. Berrospide, Correa, Goldberg, & Niepmann, 2016; J. M. Berrospide, Black, & Keeton, 2016) For example, the International Monetary Fund (IMF) and European Central Bank (ECB) have taken interest in cross-border contagion between the major global economies as part of their chartered mandate. The ECB has found that systemic risk in the US is greater than in Europe and has increased gradually since 1990 (Straetmans, Hartmann, & de Vries, 2005). On the other hand, in its pioneer research publication on contagion risk using Extreme Value Theory, the

IMF found that the contagion risk among big banks displays a generic home bias, whereas smaller banks are more likely to be affected by their larger counterparts (Chan-Lau, Mitra, & Ong, 2012; Ong, Mitra, & Chan-Lau, 2007). Given this scenario, the IMF has pushed for higher cross-border co-operation on banking supervision to control any future damage arising from spillover risk (Cihak & Ong, 2007). A more recent paper on the same issue and methodology by the Organisation for Economic Co-operation and Development (OECD) confirms the previous findings (Blundell-Wignall & Roulet, 2013).

This research differs from previous studies in terms of innovation, methodology, practical implications and coverage. Previous studies in this field mostly focused on three methodologies – cross-country correlation (CCC), vector auto-regression (VAR) and Extreme Value Theory (EVT) to study contagion in various micro- or macro-level setups. But CCC- and VAR-based models have been discovered to have serious limitations (Boyer, Kumagai, & Yuan, 2006; Forbes & Rigobon, 2002). CCC-based studies have mistakenly identified market co-movement as contagion across different entities (Akhter & Daly, 2017). They also have a synthetic upward bias in their correlation coefficient result, created by the hyper-volatility of their sample. Their results are also affected by the feedback effect and common shocks of the model (Forbes & Rigobon, 2002). The early 1990s saw an increase in interest in the Extreme Value Theory framework in regard to transmitting volatility between different markets and countries (M. Baker, Wurgler, & Yuan, 2012), given EVT's ability to understand the association of concurrent extreme events or co-exceedances across different geographical settings (Jobst, 2014). At the same time, it has the ability to capture the transmission of large shocks within the prescribed model boundaries (Dias, 2014). In this thesis, EVT framework has been used given its inherent ability to capture the differences between the impacts of large and small shocks on the underlying entity, and thus may offer a new viewpoint on cross-border contagion (Bollerslev & Todorov, 2014; Kellner & Gatzert, 2013; Tolikas, 2014). However, other distance to risk measures have also been introduced (Distance to default, distance to inefficiency and distance to capital) to study contagion, where past researchers used only distance to default. To the best of the researcher’s knowledge, there are no previous studies that specifically employ distance to inefficiency (DI) and distance to capital (DC) measures along with the measure of distance to default (DD) to investigate the contagion risk of banks at global and local level.

1.3 Research Objective

As stated above, this thesis investigates contagion risk for the global and local banking environment using three different distance to risk measures (DD, DI and DC). The research question can be states as “Is there any systemic risk spill over among the sample entities’ of this research?” In order to achieve this research goal, the research has been divided into three major parts to study the contagion effect in the global and local banking sector. In the first part (Chapter 4), the thesis researches contagion effect among the largest 20 economies of the world. The sample consists of 91 banks from 20 countries across the globe, including all

G8[1] and BRICS[2] countries. A list of all these countries and their corresponding banks is included later in the thesis. The sample also includes all the G-SIB[3] (Global systematically important banks) banks, excluding Group BPCE of France (given that Group BPCE originated in 2009 with the merger of Caisse nationale des caisses d'épargne and Banque fédérale des banques populaires). Netaxis has been taken as a substitute for Group BPCE, which is also the primary subsidiary of this deducted bank. In the second part (Chapter 5), the thesis looks into local contagion by studying the spillover among the top 15 US states. The sample consists of the four largest banks from each of the 15 sample US states. A list of these banks is provided in the sample description section. Finally, in Chapter 6, using the same 60 banks from US, a cross-bank spillover analysis is performed.

Moving on, in this research, DD, DI and DC are introduced as systemic risk measurement created by the option pricing theory (Merton, 1976). These distance to risk methods are defined as the theoretical difference between the entity's current and breakeven risk position. Distance to default is the difference between the current and default position; distance to inefficiency is the difference between the current and inefficient position; and distance to capital is the difference

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[1] Refers to the group of eight strongest economies of the world: Canada, France, Germany, Italy, Japan, Russia, the United Kingdom and the United States.

[2] Refers to Brazil, Russia, India, China and South Africa as the top most developing countries of the world. The study has excluded Russia because of highly volatile nature of their banking sector data.

[3] Global systematically important banks refer to the large financial entities which are operating in multiple countries and are considered too big to fail.

between the current and default capital threshold position. Any position lower than this distance to risk measures is considered undesirable for the entity. The procedure gives 2606 daily observations for each of these different distance to risk measures for each bank in the sample over approximately 10 financial years, from 2006 to 2015. In the next step, the probability of experiencing extreme shocks in these distance measures of contagion risk using EVT is calculated. The model then categorise these extreme shocks into sub-groups for the first two parts and keep the extreme shock unchanged for the last part of the research, where the thesis examines the contagion risk arising from the movement of these extreme systemic shocks all through the US and global baking environment using a multinomial logistic regression model (MLM). Some mutual underlying variables of the banking system variability has also been chose for the first two parts of this thesis to study their influence upon the sample states' and countries' financial health.

1.4. Structure of the thesis

The thesis is structured in eight chapters, as briefly outlined below.

Chapter 1 – Introduction. Sets out the foundation and the beginning of the thesis. This chapter encapsulates the research by providing a theoretical background and a discussion on what can be anticipated from the thesis.

Chapter 2– Literature review. This chapter deals with the previous academic contributions to the subject of contagion in the financial environment. Most articles significant to the research have been collected and communicated in a systematic manner to clarify the research agenda. The chapter identifies a need for broader research into contagion risk analysis on a global scale.

Chapter 3 – Research methodology. This chapter discusses the research procedures used in this thesis. It describes the methodology related to calculation of DD, DI and DC using the Black Scholes Option Pricing model as proxy of systemic risk then how to use multinomial logistic regression model to look into possible contagion in the global banking sector using these different measures of systemic risk as input variable. This procedure opens up a completely new avenue of systemic risk calculation for academics and practitioners. The emphasis here is on the procedures used by previous researchers and connecting them to the research goals identified in Chapter 1.

Chapter 4 – Contagion risk in the global banking sector. This chapter investigates contagion risk for the global banking environment using three different distance to risk measures (DD, DI and DC) described in the methodology section.

Chapter 5 – Local contagion risk in US banking. This chapter investigates contagion risk for the local (US) interstate banking environment using three different distance to risk measures (DD, DI and DC) described in the methodology section.

Chapter 6 – Interbank contagion in US. This chapter discusses the contagion risk for the US banking sector divided by sixty of their largest banks using three assorted distance to risk procedures (DD, DI and DC) described at the methodology.

Chapter 7 – Recommendations: Contagion Risk, Regulation and Risk Management. This chapter takes a deep look inside the findings of the previous three body chapters and brings together all of the findings to create a modern-day risk management and risk regulation framework at both micro- and macro-levels.

Chapter 8 – Conclusion. The final chapter summarises the total research discoveries from all the chapters, recapitulates the findings, limitations and future research agenda.

Chapter 2. Literature Review

2.1. Introduction

In this chapter, a semi-systematic literature review on the topic of “financial contagion” and “risk management” is undertaken as part of the thesis. In this regard, the study has systemically explored the publications of previous researchers in the field of contagion risk analysis and later synthesise them for a clearer research agenda. The objective is to look into the concept of modern day risk and its connection to the contagious nature of global banking industry by charting the movement of value shocks with in the global and local banking sector.

2.2. Conceptualisation of the key terminologies

2.2.1. Contagion

Contagion is generally described as an extreme domino effect, where the failure of one financial intermediary causes failure of a whole financial network with in that particular geographical location (Akhtaruzzaman & Shamsuddin, 2016; Freixas et al., 2015). Other authors take a more macro approach in which contagion occurs when economic shock of one country moves into another country, causing a spillover effect among the economies (Carlson & Wheelock, 2016a; Dornbusch, Park, & Claessens, 2000). It thus triggers a financial catastrophe or increases the likelihood of a financial catastrophe. As an example, at the time of global financial crisis there was a total breakdown of the global credit mechanism and failure across all the financial industries, including banking, mortgage and equity sectors. This was the single biggest example of contagion in the study’s time frame (Mensi, Hammoudeh, Nguyen, & Kang, 2016). In some ways, contagion is a cycle where the financial stress depends on the fragility of the banking system, and the fragility of the banking system in turn depends on the extent of the contagious effect, thus allowing the risk to move from one financial institution to another in a very short time. For example, at the beginning of the GFC, large banks pulled their money out of other banks and investments to limit their losses; this moved the shock from one bank to another, a perfect example of contagious spillover. Academics have stated that this contagion effect, and the failure of credit agencies with financial intermediation services, caused the greatest financial meltdown in history (Aloui et al., 2011).

2.2.2. Risk in banking

Risk has been defined in numerous ways in relation to financial services (Douglas & Wildavsky, 1983). If examined current approaches to risk, one will see a highly methodological field employing complex mathematics to reduce risks to statistics and dimensions (Power, 2008). Researchers have described the core of risk as the negative effect of uncertainty (He, Li, Wei, & Yu, 2013). This has implications for the mechanisms of risk management which have been created based on a different understanding of risk (Deguest, Martellini, & Meucci, 2013).

The goal of this section is to provide a broad review of the literature on the concept of risk from a methodological point of view. Different researchers have different point of view when it comes to explaining risk. McGoun (1995) has explored the concept through financial products and markets. Another approach is to examine systematic financial risk associated with the banking sector (Shah,

1997) where researchers have used available boundaries to define risk. However, the very nature of risk, varying and idiosyncratic, is the biggest obstacle in this regard. Thus, to identify and define risk one must look inside the mechanism of risk. A key example of this strategy is the reduction of regulation for financial entities (Reinhart & Rogoff, 2009). The following table shows definitions of risk used by previous authors and researchers, with critical analysis.

Table 2.1. Definitions of Risk

Author and Year published		Definition	Country or Settings	Critical analysis
1	Markowitz, 1952	Variance of return.	USA	The definition is too subjective. It totally excludes objective perceptions of risk.
2	Holton, 2004	Risk is a human condition which cannot be observed by organisations.	USA	Undermines the whole conceptualisation of modern financial risk frameworks.
3	He et al., 2013	The negative effect of uncertainty.	USA	Like previous authors, too subjective a definition.
4	Douglas and Wildavsky, 1983	Combined creation of knowledge about the future and agreement about the relative status of certain consequences.	USA	Too complex to use in financial field given the abstract ideology.

Looking at the table, the main challenge is to bring all the definitions together into one formulation. Thus, when it comes to defining the characteristics of the modern day concept of risk, Baker (2015) argued that

> Risk is a highly subjective idea which requires knowledge of alternative value and activities. It is primarily a social and cultural phenomenon. Finance's determination to 'objectify' it and 'measure' selective aspects of risk is shown to be biased and driven by hidden operational imperatives rather than fundamental scientific goals. It seems to be ideologically motivated by a desire to protect a particular academic hegemony in finance.

He further added that, in order to understand risk, one must look into the subdivision of risks that are currently in use (C. R. Baker, 2015; Eiteman, Stonehill, & Moffett, 2016; Hopkin, 2018), pointing to the following topics for further academic research and discussion:

- Individual preferences and attitudes (Risk adverse, risk neutral, risk seeker).
- Portfolio theory – risk as variance of return; risk reduction through diversification; Beta risk and the Capital Asset Pricing Model.
- Option volatility and the risk of derivative securities – Black-Scholes Option Pricing model.
- Measuring risk using probability theory or state-preference theory.
- Risk management (hedging strategies).
- Bond duration and volatility.
- Portfolio insurance.

- Different types of risk (e.g. interest rate risk, market risk, credit/default risk).

This shows how risk has truly become a cross-sectional concept. On the other hand, there are researchers who object to this ideology of defining risk. These authors have described risk as more a macro social phenomenon (Kasperson et al., 1988; Rasmussen, 1997). Based on all these judgements, Dionne (2013) devided modern day financial risk into following categories:

- pure risk (insurable or not, and not necessarily exogenous in the presence of moral hazard);
- market risk (variation in prices of commodities, exchange rates, asset returns);
- default risk (probability of default, recovery rate, exposure at default);
- operational risk (employee errors, fraud, IT system breakdown); and
- liquidity risk (risk of not possessing sufficient funds to meet short-term financial obligations without affecting prices).

Working within similar frameworks, most researchers have divided risks specific to the banking industry into eight categories: credit, market, operational, liquidity, reputational, business, moral hazard and systematic risk. The following paragraphs briefly describe these risk categories in more detail.

Credit risk is regarded as the most important of the eight categories for banks (Longstaff, Pan, Pedersen, & Singleton, 2011). It has many variations, but the underlying concept is the same. It is the risk of debtors' failure to repay a loan or meet contractual obligations, with potentially significant financial impacts. It arises whenever a borrower is expecting to use future cash flows to repay an existing debt. For most banks, balance sheet credits are the major and most recognisable symbol of credit risk. Still, there are other forms of credit risk, both on and off the balance sheet; for example, like letters of credit, unfunded loan commitments, lines of credit, credit derivatives, foreign exchange and cash management services (Committee, 2010).

Market risk incorporates the risk of monetary forfeiture caused by negative movements in market prices. It is rated based upon, but not restricted to, a valuation of limited estimation features (Hannoun, 2010), namely the commercial assessment of capital, which is subject to adverse fluctuations in interest rates, foreign exchange rates, commodity prices and equity prices in stock markets. In US, the market risk is calculated through the Federal Reserve's Market Risk Rule (MRR), which sets supervisory capital requirements for all Bank Holding Companies (BHCs) and state member banks (together known as banking establishments). The MRR also sets out specific key market-risk supervision requirements for banks, using stress testing and autonomous market risk management (Malloy, 2011).

Operational risk arises from the prospect that poor technological infrastructure, operational glitches, cracks in internal controls, fraud or other unforeseen calamities will result in unexpected losses. The concept of operational risk was identified in the BASEL II regulations. It is also described as hybrid risk and associated with operations across multiple environments (Barakat & Hussainey, 2013). It unites many contemporary "risk and control issues" – fraudulent practice, system error, product line discontinuation effects and human resource disputes, as well as strategic infrastructure risk. It is unique in spanning capital management and corporate governance issues at a macro level.

Liquidity is a bank's ability to meet its cash and collateral commitments without experiencing undesirable losses (Drehmann & Nikolaou, 2013). Satisfactory liquidity is reliant upon the organisation's capacity to meet both anticipated and unexpected cash flows and indemnity requirements without adversely affecting the daily operations of the bank (Cornett, McNutt, Strahan, & Tehranian, 2011). As most banks use a substantial amount of leverage in their running operations, and are obligated to meet promised debts in order to maintain the confidence of clients and fund benefactors, liquidity risk control is crucial to a bank's productivity and trustworthiness (V. Acharya & Naqvi, 2012). Fund managers have divided liquidity risk into two aspects – market liquidity risk (market liquidity deteriorates when one is required to unwind a position) and funding liquidity risk (a bank cannot fund its position and is required to unwind). BASEL uses two ratios to calculate and control liquidity risk, the liquidity coverage ratio and net stable funding ratio (Supervision, 2010). Nevertheless, there are other ways to calculate and control liquidity risk. Market liquidity risk can be calculated or measured in three ways – bid–ask spread, market depth and market resiliency, while funding liquidity risk can be measured through margin funding risk, rollover risk and redemption risk.

Reputational risk is defined as the threat arising from adverse perceptions on the part of clients, stockholders, financiers, debt-holders, market experts, industry regulators and other relevant parties, and can adversely affect a bank's capacity to sustain existing, or inaugurate new, business associations and access to sources of capital (Cantor, 2001). The issue of reputational risk has never been more important than at present, given the increase in reporting of fraudulent activities by banks in the last decade or so (e.g. Allied Irish Bank, Barings and Daiwa Bank Ltd, The Republic New York Corp etc.). Previous researchers have identified six underlying or contributing factors of reputational risk: bank riskiness, profitability, level of intangible assets, capitalisation, size, the source of operational loss and the business units that suffer operational loss (Fiordelisi, Soana, & Schwizer, 2013). This is consistent with the common view that reputational risk is multidimensional and reflects the perception of other market participants (Sturm, 2013).

Business risk is more commonly known as non-systematic or diversifiable risk. It is the risk attributable to business elements that affect all business, and it can be eradicated through diversification of the firm’s portfolio. It is the mathematically calculated residual risk after deducting the market or systematic risk. The asset pricing model, more commonly known as the capital asset pricing model (CAPM), first provided the theoretical linkage to non-systematic or non-diversifiable risk (Dempsey, 2013), which was subsequently elaborated through the Black-Scholes model (Albrecher, Binder, Lautscham, & Mayer, 2013). Most previous researchers recognised that, given its entity-specific nature, business risk is largely unique to each financial institution (McNeil, Frey, & Embrechts, 2015).

Systematic risk, or market risk, is the portion of risk that cannot be diversified through market operations given its macro-level impact. This thesis deals specifically with this sub-division of risk using three different distance-to-risk measures. The modern corporate world largely relies on two measures of systematic risk, the Value-at-Risk (VaR) and Expected Shortfall (ES) methods (Kratz, Lok, & McNeil, 2018; Krause & Paolella, 2014; May & Arinaminpathy, 2010). These models generate the residual of total risk minus non-systematic risk to define systemic risk. Individual banks cannot totally protect themselves from systematic risk given the interconnected nature of the current global banking industry (Ariss, 2010). Previous writers have identified numerous factors as contributors to this risk – alterations in investment policy, foreign investment strategy, modifications in taxation clauses, altering of socioeconomic considerations, international security threats etc. (Ewens, Jones, & Rhodes-Kropf, 2013; Hall & Woodward, 2010). Researchers have also shown that it is difficult to find a systemic risk measure that is at the same time both relevant and totally acceptable by a general equilibrium model (V. V. Acharya, Pedersen, Philippon, & Richardson, 2010). The problem is the gap between academic models and the requirements for application by regulators. To overcome these shortcomings, this study uses three different measures of systematic risk (distance to default, distance to inefficiency and distance to capital) rather than VAR and ES. Detailed descriptions of these measures are provided in subsequent chapters.

Moral hazard risk is the risk created by a lack of ethical standards in financial the industry. It is being described as a state in which a firm gets involved in high-risk activities with hedged protection against that risk, meaning that in the end only the other party will experience any loss (Dam & Koetter, 2012). Like other abstract risks, it is hard to measure moral hazard in an quantifiable way (Farhi & Tirole, 2012), although in insurance price elasticity of demand has been used to calculate moral hazard (Joseph, 1972). As identified by previous researchers, the scope of moral hazard hinges on the sensitivity of the hedged position and price changes (Boyd & De Nicolo, 2005).

2.2.3. Risk management

Risk management is defined as a set of financial or operational mechanisms that maximise the value of a company or a portfolio by maintaining the costs associated with cash flow volatility (Stulz, 2003). The goal of modern-day risk management is to create a reference framework to control risk and uncertainty (Dionne, 2013). It should be integrated to provide total control over evaluating and monitoring all uncertainties in the institution. Figure 2.1 shows the currently used ISO 31000 risk management framework (Purdy, 2010).

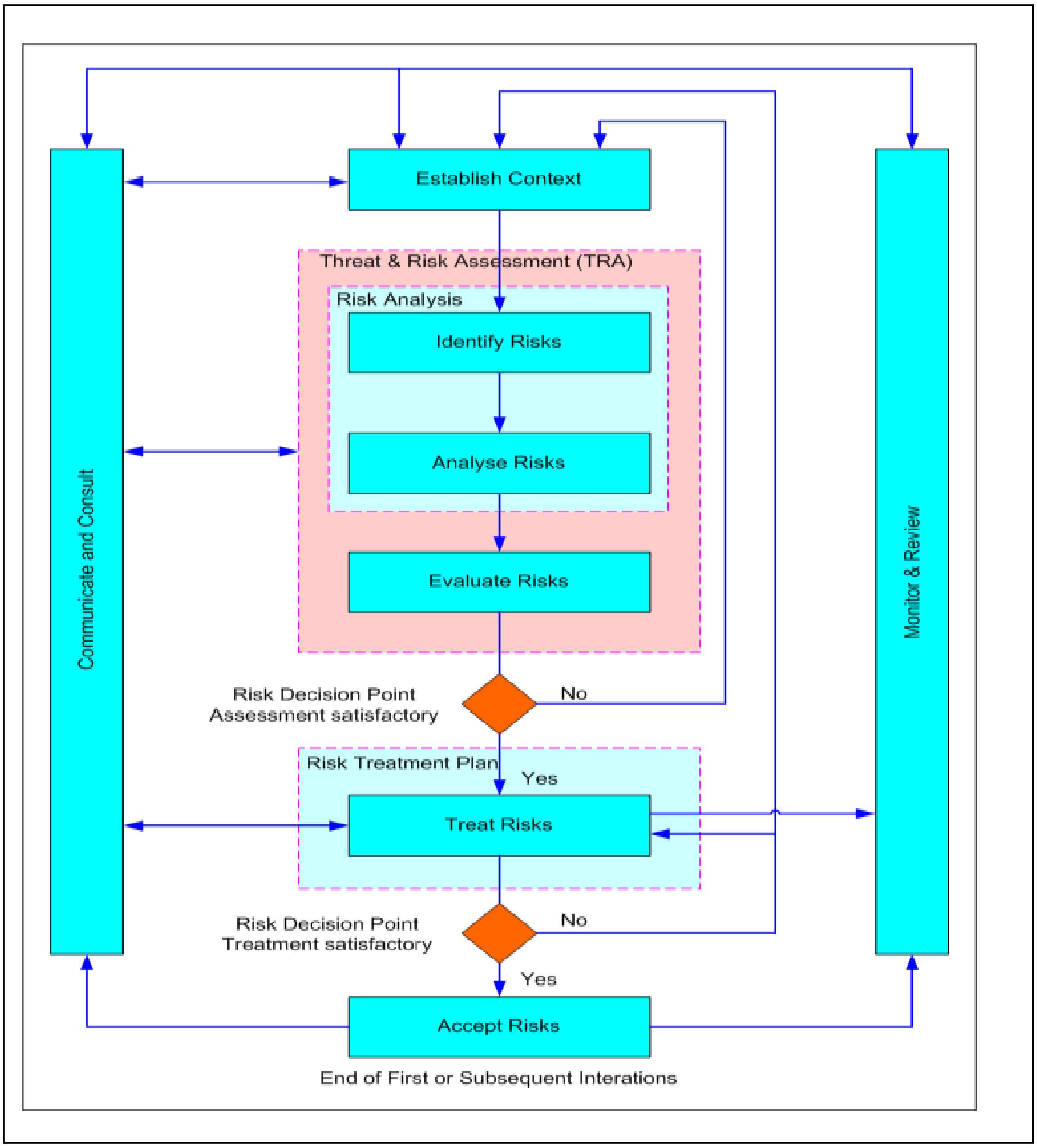


Figure 2.1. Risk Management Framework ISO 31000

Previous researchers have noted that measurable risk is controllable risk, thus connecting measurement and management of risk (Das, 2011). This view is reflected in the embedded nature of modern day risk management practices by institutions (Hayne & Free, 2014; Power, 2008), albeit not always successfully – forensic analysis has shown that the inability to understand risk was one of the precipitators of the global failure of financial institutions during the GFC (Peston, 2008). The birth of modern-day risk management can attributed to Markowitz, who first proposed measuring risk using standard deviations, assuming they are normally distributed (Markowitz, 1952). The total risk scenario can easily be described by two variables, standard deviation and mean. This definition eliminates the impact of social or individual influences on risk management. Haldane (2012) has argued that this avoidance of uncertainty in the speculative models, and assumptions of rational behaviour, are a key flaw in the understanding of risk management (Haldane & Madouros, 2012).

The following table includes some of the most prominent definitions of risk management used by modern theorists.

Table 2.2.3.1 - Risk Management definitions

Author and Year published		Definition	Country or Settings	Critical analysis
1	Stulz, 2003	A set of financial or operative events that maximise the value of a company or a portfolio by reducing the costs associated with cash flow volatility.	USA	A pure mathematical model not appealing enough to control abstract risk or human factors of risk.
2	Dionne, 2013	The goal of modern day risk management is to create a reference framework to control risk and uncertainty.	World	A good overview of risk management but too abstract.
3	Kalia and Müller, 2007	The permanent and systematic recording of all kinds of risks with regard to the existence and the development of the	Europe	Too abstract in nature for modern-day application.

		enterprise; it involves analysing and prioritising recognised risks as well as defining and implementing adequate strategic or operational measures to minimise non-tolerable risks. It is a holistic process that encompasses a modular cycle of communication, documentation, control, early warning and advancement.		

2.2.4. Risk management techniques used by the banks

Banks have had the same risk management objective since the beginning of the financial industry – reducing risk but not profit. Thus, the true objective of risk management practices in financial institutions is to identify current risk and decide how much of that risk the organisation needs to manage or minimise. But in recent years –following the GFC – the banking industry has undergone significant change in practices, particularly in the areas of risk-based governance structures and lending practices (Calomiris & Carlson, 2016). In its latest study, the Institute of International Finance has proposed three issues as key managerial concerns for a sound risk management approach for global banks – impact of regulations on business models, market volatility and sovereign debt crisis (Finance, 2012). Adding to that, other researchers have suggested banks need to work on several areas – role of boards, role of chief risk officers, size and skill level of risk teams, risk evaluation models, liquidity management, stress testing, risk-based culture and coping with regulatory reforms – to maintain a sound position (Huang, Zhou, & Zhu, 2012; Imbierowicz & Rauch, 2014). Examining these issues, the study has found that the key drivers of contemporary risk management practices are designed to meet global financial challenges, such as increased economic pressure in US and UK, the European debt crisis and the ever-changing regulatory environment of the modern technological world (Reason, 2016). The increased capital and liquidity buffers implemented through BASEL are also permanently changing the playing field (Dowd, Hutchinson, & Ashby, 2011). Despite these efforts, however, extant risk management tools and techniques have yet to produce the confidence stakeholders are seeking after the global financial crisis (Levine, 2012).

If one looks into the central risk management framework from a more practical, implementation viewpoint, one will find that previous researchers have mentioned many models – the three lines of defence model (Straub & Welke, 1998), the offence and defence model made of front line employees, compliance and external auditors (Sweeting, 2011), the policy and policing model made of check and balance (Caballero & Krishnamurthy, 2006) and the partnership model based on working together for a common goal (Grimsey & Lewis, 2002). Taking these frameworks together, the risk management of banks can be divided into several steps – identifying risk, quantifying risk, assessing risk, responding to risk and continuous progression. These steps – currently being implemented by financial regulators through adaptation of the BASEL III global regulatory framework for banks – are described in the following paragraphs.

The first step of the risk identification process is to create a checklist (using quantitative or qualitative process) of which of the many possible risks are currently affecting the productivity bottom-line (Gorzeń-Mitka, 2013). Researchers have noted that this should be a well-defined process with proper recording procedures. Thus, the identification process can be further subdivided into tools, assessments and recording. Given the current knowledge base on risk analysis, most banks will use SWOT (Strengths, Weakness, Opportunities and Threats) analysis, risk checklists, risk trigger check-ups or risk taxa logy to identify the risks. Researchers have confirmed that surveys, gap analysis and the Delphi technique are also widely used in that regard (Rowe & Wright, 2011). The results are then transferred to a risk register, with specific identification, measures and descriptions of the risks including identifier, category, description, quantification, severity, exposure, current status, linkage, cost, response, timetable and overall process (Pritchard & PMP, 2014).

The second step is quantifying risk, which is the core principle of modern risk management (Cunningham, Herzog, & London, 2012). Examples of quantification in modern risk processes include market and liquidity risk measurement. Most banks use Greek letter-based mechanisms to measure market risk. Thus, the delta (Δ) of a portfolio is the degree of modification with respect to the value of the underlying portfolio. Managing risk through delta hedging includes generating a position which produces a delta that is neutral or zero (Gobet & Makhlouf, 2012). Another common measure is gamma, which is the percentage change in delta, and a third measure is vega. The last two can be controlled by trading options on the bank's asset base (Natenberg, 2014). BASEL III prescribes the use of two ratios for liquidity risk, Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). The LCR emphasises a bank's capacity to endure a 30-day period of extreme liquidity stress. It is calculated as: High-Quality Liquid Assets divided by Net Cash Outflows in a 30-Day Period. NSFR is longer-term, looking at a period of 12 months. It is calculated by Amount of Stable Funding divided by Required Amount of Stable Funding.

The next stage of risk management involves assessing risk. It can be defined as "trying to observe the effect of maximum risk" on the banking organisation within different parameters (Higgins et al., 2011) by evaluating different prospective or retrospective risk and return (income and capital) measures. A common measurement of risk assessment is risk tolerance (Sahm, 2012). Risk tolerance can be shown using a utility function and shows the theoretical risk tolerance of the bank. Mostly it will be expressed as a utility or preference function, such as:

$\delta 2 > \delta 1$, $[u(W + \delta 1) - u(W)]/\delta 1 > [u(W + \delta 2) - u(W)]/\delta 2)$ (2.2.4.1)

Where u stands for utility, W is wealth and δ is risk tolerance. Based on this measure, one can create three different utility functions to express the trade-off between risk and return – quadratic (2.2.4.2), exponential (2.2.4.3) and power utility (2.2.4.4).

$u(W) = \alpha E(W) - 1/2 * E(W2)$ (Where $W \leq \alpha$, 2.2.4.2)

$u(W) = -e - e^{-\alpha w} / \alpha$ (Where $\alpha > 0$, 2.2.4.3)

$$u(W) = \{ \begin{matrix} \frac{W^{1-\alpha}}{1-\alpha} \; if \; \alpha > 0 \; and \; \alpha \neq 1 \\ In \, W \quad if \; \alpha = 1 \end{matrix} \left(where \; a(W) = \frac{\alpha}{W} \right) \quad (2.2.4.4)$$

Additionally, volatility measured by standard deviation is another common measure of risk. It is defined as the difference between actual and standard performance benchmarks in a portfolio context (Bollerslev, Gibson, & Zhou, 2011). In equation 2.2.4.5, the volatility is measured through standard deviation of returns assuming the average return is more than zero given most business will try to make a profit.

$$\text{Volatility} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (r_{x,t} - r_{B,t})^2} \quad (2.2.4.5)$$

But the most acceptable way to measure financial risk is the calculation of VaR or value at risk (Hubbert, 2012). Sometimes this is also defined as the absolute monetary loss, as in equation 2.2.4.6.

$$\text{VaR} = W_0 - (1+\alpha_C)W_0 = -\alpha_C W_0 \qquad (2.2.4.6)$$

Where $W_0 \ldots$ original portfolio's price (financial amount), α_C = Cut-off rate of return for given CI, and $\alpha_C W_0$ = Loss analogous to the cut-off rate of return (financial amount).

Once the first three steps (identifying risk, quantifying risk and assessing risk) are complete, a financial institution will move to risk minimisation or responding to risk. This involves taking steps before the risk event to minimise or control the possible downside (Ellul & Yerramilli, 2013). Previous researchers on risk management theory have shown numerous ways to reduce risk for a bank, ranging from diversification to risk transfer. These mechanisms can be divided into three parts: insurances, internal control and external control.

The oldest way to ensure protection from financial risk is the insurance policy (Trenerry, 1926). A bank can protect itself against any risk through insurance up to a certain celling (Ai, Brockett, Cooper, & Golden, 2012). But it can be very costly and there are regulatory limitations. The trend over the past two decades indicates the banking industry is gradually losing interest in insurance as the primary instrument of risk management and moving more towards internal control mechanisms. This refers to organisational activities to prevent the risk event before it occurs using policies, procedures and limits (Nurullah & Staikouras, 2015). All these measures are non-capital market-based and non-investment based mechanisms. Measures like corporate governance practices have become a key ingredient in this regard in the wake of the global financial crisis (Erkens, Hung, & Matos, 2012). The third and final risk response can be described as an external measure, where the financial institutions use financial products and investment strategy to minimise risk. Some of the most-used methods in this regard are diversification, increasing efficiency and hedging with derivatives such as options and futures. All these risk-managing instruments are used to create the global regulatory framework for the banks and financial institutions known as Basel Accord.

2.2.5. Regulation – BASEL

Basel, or the Basel Accords, is the key financial regulatory framework for all banking entities. The core aim of Basel is to increase the inherent stability and soundness of banks, given considering their impact at the macro-economic level (Sutorova & Teplý, 2013). By connecting the banking sector with legal framework, it attaches the financial entities directly to global liquidity and capital control mechanisms, which can be very helpful in times of financial distress (Gleeson, 2010). Previous writers have also tied Basel in with economic development and large-scale poverty reduction (Calice, 2010). In this thesis, the methodology uses one of the most prominent safeguards from the Basel Accord – mandatory capital adequacy ratio of 8% to calculate distance to capital, which is part of the core methodology of this research.

2.2.5.1. Basel I – The Credit and Market risk

The Basel committee was first formed in 1974 by the central bank regulators of the top ten global economies in the aftermath of the failure of the Germany's prominent Bankhaus Herstatt (Levinson, 2010). The committee's objectives were to set minimum criteria for central banks and standard-setting organisations all over the world on regulatory matters, tactics and practices; to endorse common understanding; to progress cross-border collaboration; and to help classify developing risks in the banking system. Their first achievement on a global level was the 1975 Basel Concordat. It was created to ensure global banks operated under adequate supervision, which set the stage for further development of high quality, coordinated banking supervision in participatory countries. The core focus subsequently moved to the issue of capital adequacy in order to protect general stakeholders in the financial system. It was found that the capital ratios of the global banks were decreasing at a rapid rate because of heightened political and financial stability risk, demonstrating the need for risk measurement using both on and off balance-sheet bank activities. Taking all of this into consideration, the committee published the first regulation accord, or Basel I, in 1988. They key feature of this accord was the requirement for minimum capital to risk weighted assets to be standardised at 8% by 1992 in all international banks. The Basel framework was periodically readjusted time to reflect the evolution of global regulation and capital adequacy. At the end of 1991, definitions of loan loss reserve were published for improved calculation standards in capital adequacy requirement. In late 1995, they made another adjustment to recognise the bilateral netting of banks' credit risk in derivatives with the adding matrix factors. In 1997, they added market risk to the previous credit risk, which introduced the value at risk or VaR model to measure capital requirement based on market risk exposure.

2.2.5.2. Basel II – Inclusion of trading books

From 1998 through 2004, the Basel committee undertook intensive research on global banking regulation, using in-depth interviews with banking sector legislatures, managerial agencies, central banks and stakeholders. Their objective was to increase the regulatory boundaries for better risk management. In the middle of 2004, they issued a new standard, known as Basel II (I. Basel, 2010). This comprised three pillars or focal points for regulation – minimum capital requirement (as in the previous 1988 accord), supervisory review of internal capital adequacy and effective disclosure based on sound practices. In 2005, they added the regulation of trading books to banking or accounting books and published a comprehensive version of another set of revised standards, with the help of International Organization of Securities Commissions (IOSCO).

2.2.5.3. Basel III – After the GFC

During and after the global financial crisis, the need for consolidation of the Basel II charter became obvious; a combination of excessive leverage, inadequate liquidity buffers and poor governance undermined risk management practices and, together with questionable incentive structures, created a crisis that literally reduced global by half (Claessens, Dell'Ariccia, Igan, & Laeven, 2010). Supported by the G20 leaders, at the end of 2010 the latest version of the regulations was introduced as Basel III, a global regulatory framework for more resilient banks and banking systems. It included considerable changes from the past standards to protect the global financial system from another crisis. Basel III added another layer of common equity as a capital conversion buffer. It restricted the payouts of earnings to protect the minimum common equity threshold. A countercyclical capital buffer was enforced to ensure banks did not participate in credit booms thus protecting them from credit busts. It also introduced leverage ratio, measured as a least amount of loss-absorbing capital comparative to bank's assets and off-balance sheet risk exposures. Liquidity coverage ratio and net stable funding ratio were two other key aspects of Basel III. Liquidity coverage ratio covers the company's cash requirement for a high-stress 30-day period and net stable funding ration address the maturity mismatch. Other elements of Basel III included supplementary and contingent capital increase with reinforced cross-border regulation. In the thesis's methodology, the study has incorporated the capital adequacy ratio from Basel III (BIS, 2017).

2.2.6. Contagion risk

The issue of financial contagion in the banking sector is not a new concept (Feldkircher, 2014; Hasman, 2013; Kenourgios & Dimitriou, 2015; Ladley, 2013). Previous writers have explored the impact of contagion in the financial sector from different viewpoints and using various parameters (Carlson & Wheelock, 2016b; Hasman, 2013; Ladley, 2013; Tonzer, 2015). They have also looked into the origin of the contagion risk and its movement through the global economy. As part of their core mandate, the International Monetary Fund (IMF) and European Central Bank (ECB) have been working for several decades on geographical contagion between the global and local economic powerhouses. The ECB has found that financial spillover risk in the US is much higher than in Europe. It also pointed out that the risks associated with contagion from the US have been gradually increasing since 1990 (Straetmans et al., 2005). The IMF focused more on the interbank spillover risk among the larger banks of the world, particularly the global systematically important banks (G-SIBs). It found that these big banks show an improvised home bias and tend to move their value shocks to their smaller counterparts in the same region (Chan-Lau et al., 2012; Ong et al., 2007). Consequently, the IMF advised financial regulators to push for greater cross-border co-operation on regulatory supervision to control any future shocks arising from contagion risk (Cihak & Ong, 2007). These findings have been seconded by other global regulators (Blundell-Wignall & Roulet, 2013).

2.3. Findings and conclusion

The chapter started by defining contagion and then moved on to risk management and the Basel framework, finishing with a conceptual review of contagion risk. The purpose of the chapter is to provide a basic understanding of these terminologies and what previous writers have found in their research. In summary, contagion risk can be defined as an extreme macro implication of uncertainties due to spillover between different entities, ranging from individual banks up to countries. The chapter concludes that, by understanding the nature of contagiousness within the banking industry considered both globally and within countries, one can minimise the value degradation arising from these sorts of risks. Thus, the objective of this thesis is to examine the nature of contagion within the global and local banking industry and to identify the movement of value shocks within the sector to understand the contagion risk arising spillover.

Chapter 3. Methodology

3.1. Introduction

Most previous studies dealing with the contagion effect across micro or macro level entities have used generalised autoregressive conditional heteroscedasticity (GARCH)-type volatility to define the volatility of one entity in terms of the volatility of others (Dungey, Milunovich, Thorp, & Yang, 2015; Primiceri, 2005). But the beginning of 1990s witnessed an increased interest in extreme value theory-based frameworks focusing on contagion risk analysis between different markets and countries (M. Baker et al., 2012; Rocco, 2014). These extreme value theory-based models focus on the end of the distribution (using outliers at a specific confidence interval mostly at 5% or 10%) to analyse the pattern of the underlying variable (Diebold, Schuermann, & Stroughair, 2000). For example, researchers found that the behaviour of the maxima (asymptotic behaviour of the extreme realizations) is dependent on the three extreme value distributions (Fisher & Tippett, 1928). Past researchers have also suggested that extreme value theory (EVT) has the ability to understand the association of concurrent extreme events or co-exceedances in different geographical settings (Jobst, 2014), which can be used to capture the transmission of large extreme shocks within the prescribed model boundaries (Dias, 2014). Current researchers has used this findings in different context but for the same reason (Di Clemente, 2018; Zhu, Dekker, Van Jaarsveld, Renjie, & Koning, 2017). This study have used these specific characteristics of EVT in the thesis'smodel to measure the impact of contagion risk within global and local banking sectors following the footsteps of similar research articles in the same domain (Akhter & Hasan, 2015).

In this research, the goal is to determine whether an extreme negative shock to one financial entity[4] of the study's sample is linked to similar shocks faced by other financial entities in the sample. The study commences by determining which banks have experienced shocks, and on which dates, over the period from 6 January 2006–31 December 2015. The research parameters define a shock as an incident when an exceedance[5] occurs for a bank in a particular time. Previous studies have predominantly used only distance to default to measure the default risk (Blundell-Wignall & Roulet, 2013; Chan-Lau & Sy, 2007). However, the study uses two more recent default risk measures, distance to inefficiency and distance to capital, in this research. A detailed description of these measures (distance to default, distance to inefficiency and distance to capital) is provided later in this section. The study hypothesises that financial distress in a particular financial entity increases the probability of financial distress in other financial entities in the sample. The thesis subsequently test the hypothesis that exceedances in one financial entity are a function of exceedances in others in the sample.

To test this hypothesis, the study considers a model that inputs simultaneous exceedances or co-exceedances in the base country's or state's banking sector as the dependent variable, and the number of co-exceedances in other country's or state's banking sector – along with common shocks – as the explanatory variables. At first it examines country-to-country spillover, followed by country-to-US state and US

[4] Defined by a particular US bank or a US state represented by four banks or a country represented by key banks.

[5] When a bank outstrips a subjective extreme value. The study defines extreme value as the negative 90th percentile of the change in the distance risk measurement.

state-to-US state spillover in the second part using STATA software. For the final part of this research – interbank spillover analysis of the US –the thesis considers a model that inputs extreme shocks in the underlying US bank as the dependent variable and compares it with the extreme shocks in other US banks in the thesis's sample as the explanatory variables. The thesis allows a one-day lag for explanatory variables[6]. Then, for the first two parts of the research (intercountry and interstate contagion),the study categorises the dependent variables into four classes: tranquil (no bank exceeds the threshold of distance risk measure at a given point of time), disturbing (up to 25% of the banks exceed the threshold of distance risk measure at a given point of time), alarming (up to 50% of the banks exceed the threshold of distance risk measure at a given point of time) and crisis (over 50% of the banks exceed the threshold of distance risk measure at a given point of time). The study then inputs these variable into the multinomial logistic model (MLM) to calculate the likelihood of each of these discrete events for the base country or state given similar events occurring (allowing for a one-day lag) in other countries or states in the sample. At the same time, in this model explores the impact of several mutually explanatory variables, such as progression in the real economy (calculated using term structure spread) or volatility in national and international stock markets. For the interbank contagion analysis, the study inputs extreme shocks from banks directly into the multinomial logistic model (MLM) to calculate the likelihood of each of

[6] In accordance to the current publications in finance and banking field, any news originated in one part of the world transmitted to the other part of the world within 24 hours (Rangel, 2011). This has primarily influenced us to take the 1-day lag.

these discrete events (extreme shocks) for the base bank given similar events occurring (allowing for a one-day lag) in other banks in US.

3.2. Sample

As described before, this research is divided into three phases. In the first part, the study looks into contagion risk arising from, or spreading into, 20 different countries of the world. After that, it looks into contagion risk between the US states and between US states and countries. In the final phase, the study again looks at contagion risk into the US, but this time at bank level. All the banks in the sample are chose based on their impact on the corresponding economy (calculated by their size) and data availability on DataStream and Bank scope, if there are multiple banks in similar size then the study has choose all of them for that country or state.

For the first part of the study, the sample consists of 91 banks from 20 countries, including all G8 and BRICS countries. A list of all these countries and the corresponding banks is provided in Table 3.2.1. The sample includes all the G-SIB (global systematically important banks) group excluding Group BPCE of France (given that Group BPCE was created in 2009 by the merger of Caisse nationale des caisses d'épargne and Banque fédérale des banques populaires).The research has used Netaxis as substitute as it is the primary subsidiary of Group BPCE.

Table 3.2.1- List of sample countries and banks for the first phase

Country	Number of Bank	Name of Bank
Australia	1	AUS.AND NZ.BANKING GP.
	2	WESTPAC BANKING
	3	COMMONIALTH BK.OF AUS.
	4	NATIONAL AUS.BANK
Belgium	5	BANQUE NALE.DE BELGIQUE
	6	DEXIA
	7	KBC GROUP
	8	KEYTRADE BANK
UK	9	BARCLAYS BANK
	10	HSBC
	11	ROYAL BANK OF SCOTLAND
	12	STANDARD CHARTERED BANK
Switzerland	13	CREDIT SUISSE GROUP
	14	UBS
	15	ST GALLER KANTONALBANK
	16	BANQUE CANTON.DE GENEVE
Sweden	17	NORDEA
	18	SEB
	19	SVENSKA HANDBKN
	20	SIDBANK
Spain	21	BANCO SANTANDER
	22	BBV.ARGENTARIA

	23	BANCO DE SABADELL
	24	BANCO POPULAR ESPANOL
South Africa	25	FIRSTRAND
	26	NEDBANK GROUP
	27	CAPITEC BANK
	28	STANDARD BK.GP.
Korea	29	HANA FINANCIAL GROUP
	30	INDUSTRIAL BANK OF KOREA
	31	KB FINANCIAL GROUP
	32	SHINHAN FINL.GROUP
Netherland	33	ING GROEP
	34	BINCKBANK
	35	KAS BANK
	36	VAN LANSCHOT
Mexico	37	BANREGIO GRUPO FINANCIERO
	38	GPO FINANCE BANORTE
	39	GRUPO FINANCIERO INBURSA
	40	SANTANDER MEXICO
Malaysia	41	CIMB GROUP HOLDINGS
	42	MALAYAN BANKING
	43	RHB BANK
	44	ALLIANCE FINANCIAL GP.
Japan	45	MITSUBISHI UFJ FINL.GP.
	46	MIZUHO FINL.GP.
	47	SUMITOMO MITSUI FINL.GP.

	48	CHIBA BANK
Italy	49	UNICREDIT
	50	BANCO POPOLARE
	51	INTESA SANPAOLO
	52	UNIONE DI BANCHE ITALIAN
Germany	53	DEUTSCHE BANK
	54	COMMERZBANK
	55	OLDENBURGISCHE
	56	UMILTBANK
France	57	BNP PARIBAS
	58	CREDIT AGRICOLE
	59	NATIXIS
	60	SOCIETE GENERALE
Denmark	61	DANSKE BANK
	62	JYSKE BANK
	63	SPAR NORD BANK
	64	SYDBANK
Brazil	65	BRB BANCO DE BRASILIA
	66	BANCO DO NORD ON
	67	BANCO ESTADO ESPIRITO SANTO
	68	AMAZONIA
US	69	BANK OF AMERICA
	70	BANK OF NEW YORK MELLON
	71	CITIGROUP
	72	GOLDMAN SACHS GP.

	73	JP MORGAN
	74	MORGAN STANLEY
	75	STATE STREET
	76	ILLS FARGO & CO
India	77	BANK OF INDIA
	78	BANK OF BARODA
	79	CANARA BANK
	80	HDFC BANK
	81	ICICI BANK
	82	PUNJAB NATIONAL BANK
	83	STATE BANK OF INDIA
China	84	AGRICULTURAL BANK OF CHINA
	85	BANK OF CHINA
	86	CHINA CON.BANK
	87	CHINA MERCHANTS BANK
	88	CHINA MINSHENG BANKING
	89	HUAXIA BANK
	90	INDUSTRIAL & COML.BK.OF CHINA
	91	SHAI.PUDONG DEV.BK.

For the second and third part, the sample is comprised of four large banks from 15 different US states compromising all the GSIB banks excluding Morgan Stanley[7]. A list of all the US sates and the corresponding banks is provided in Table 3.2.2.

Table 3.2.2- List of sample countries and banks for the second and third phase

State	Number of Bank	Name of Bank
California	1	CATHAY GENERAL BANCORP INC
	2	SVB FINANCIAL GROUP
	3	ILLS FARGO & COMPANY
	4	CHARLES SCHWAB CORPORATION
Newyork	5	BANK OF NEW YORK MELLON
	6	CITIGROUP
	7	GOLDMAN SACHS
	8	JPMORGAN CHASE
Gorgia	9	AMERIS BANCORP
	10	SUNTRUST BANKS, INC.
	11	SYNOVUS FINANCIAL CORP
	12	UNITED COMMUNITY BANKS, INC
Illinois	13	FIRST BUSEY CORPORATION
	14	FIRST MIDIST BANCORP, INC
	15	MB FINANCIAL INC
	16	WINTRUST FINANCIAL CORPORATION
Indiana	17	1ST SM. CORPORATION
	18	FIRST MERCHANTS CORPORATION

[7] Given that the cut-off was the largest four banks from any one state and Morgan Stanley is the fifth largest bank in New York state.

	19	OLD NATIONAL BANCORP
	20	LAKELAND FINANCIAL CORPORATION, INDIANA
Massachusetts	21	BERKSHIRE HILLS BANCORP INC
	22	BOSTON PRIVATE FINANCIAL HOLDINGS INC
	23	BROOKLINE BANCORP INC
	24	STATE STREET CORPORATION
Michigan	25	CHEMICAL FINANCIAL CORPORATION
	26	ENTERPRISE FINANCIAL SERVICES CORP
	27	FLAGSTAR BANCORP INC
	28	INDEPENDENT BANK CORPORATION
Mississippi	29	TRUSTMARK CORPORATION
	30	BANCORPSOUTH, INC.
	31	HANCOCK HOLDING COMPANY
	32	RENASANT CORPORATION
New Jersey	33	CONNECTONE BANCORP INC
	34	LAKELAND BANCORP, INC
	35	PROVIDENT FINANCIAL SERVICES, INC.
	36	VALLEY NATIONAL BANCORP
North Carolina	37	BANK OF AMERICA CORPORATION
	38	BB&T CORPORATION
	39	FIRST CITIZENS BANCSHARES
	40	YADKIN FINANCIAL CORPORATION
Ohio	41	FIFTH THIRD BANCORP
	42	FIRST DEFIANCE FINANCIAL CORP
	43	HUNTINGTON BANCSHARES INC
	44	KEYCORP
Pennsylvania	45	NORTHIST BANCSHARES INC
	46	FULTON FINANCIAL CORPORATION

	47	FNB CORPORATION
	48	PNC FINANCIAL SERVICES GROUP INC
Taxas	49	COMERICA INCORPORATED
	50	PROSPERITY BANCSHARES, INC
	51	TEXAS CAPITAL BANCSHARES, INC
	52	CULLEN/FROST BANKERS, INC
Virginia	53	CAPITAL ONE FINANCIAL CORPORATION
	54	FREDDIE MAC
	55	TOWNE BANK
	56	UNION BANKSHARES CORPORATION
West Virginia	57	PREMIER FINANCIAL BANCORP
	58	CITY HOLDING COMPANY
	59	ISBANCO, INC
	60	UNITED BANKSHARES, INC.

3.3. Distance to risk measures

3.3.1. Distance to default

Distance to default (DD) is a cause and effect-based structural systemic risk model that represents the default risk of an entity (Saldías, 2013). The concept represents the distance between the entity’s given position and its hypothesised default position, where default is a position in which the firm’s asset value falls below the liability value threshold (Milne, 2014). Figure 3.3.1.1 illustrates the notion of DD where the horizontal (x) axis represents market value of the asset and the vertical (y) axis shows the liabilities (Akhter & Hasan, 2015).

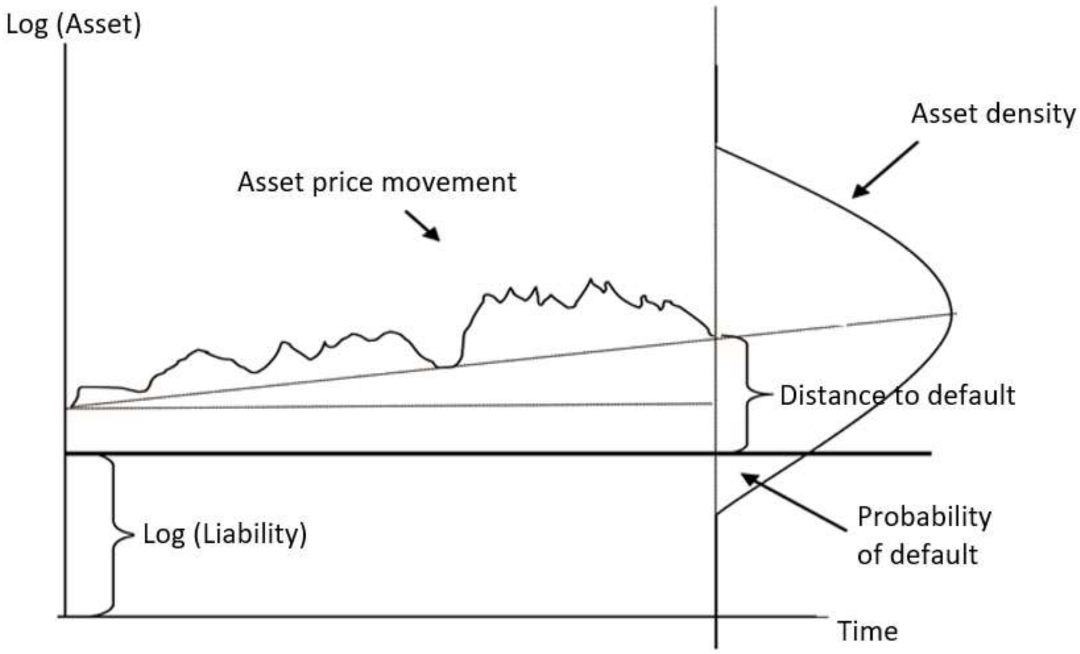


Figure 3.3.1.1. Distance to default

At t = 0 (starting point) the value (Asset = equities + liabilities) of a limited liability entity is given as $\ln A_0$ and liabilities are lnL. Theoretically, the entity defaults when $\ln A_0$ falls below lnL (as illustrated in Figure 3.3.1.1). If one assume µ is the change in the asset value in a day with spreading of σ_A^2, then the value of the entity for T-t period can be written as $Ln(A_t + (\mu - 0.5 * \sigma_A^2)(T - t)$. From that, one can derive distance to default as shown as equation 3.3.1.1.

$$DD_t = -\frac{\ln(L) - \{\ln(A_t) + \left(R_f + \frac{\sigma_A{}^2}{2}\right) \cdot (T - t)\}}{\sigma_A \cdot \sqrt{T - t}} \qquad (3.3.1.1)$$

This equation (3.3.1.1) is used to derive the daily value of DD for the model. Unfortunately, asset, liability and equity values are only available on a yearly basis from the balance sheet. To get the daily value of the asset, the study employs a simulation-based model using an option pricing formula (Black & Scholes, 1974) as prescribed by the previous authors (Akhter & Hasan, 2015). Equation 3.3.1.2 shows the equity value as price of a call option.

$$\text{Equity value (Call price)} = A_t N(d_1) - L \cdot e^{R_f \bullet (T-t)} \cdot N(d_2) \qquad (3.3.1.2)$$

$$\text{where} \quad d_1 = -\frac{\ln(L) - \{\ln(A_t) + \left(R_f + \frac{\sigma_A{}^2}{2}\right) \cdot (T-t)\}}{\sigma_A \cdot \sqrt{T-t}} \qquad (3.3.1.3)$$

$$d_2 = d_1 - \sigma_A \cdot \sqrt{T-t}. \qquad (3.3.1.4)$$

The study assumes a firm has only one unit of equity (E) and one unit of liability represented by a zero-coupon bond with face value of L and maturity T. In an ideal world, the asset value (A) should always be greater than the value of the zero-coupon bond (L); thus, equity owners obtain the enduring value. On the other hand, if the assets value (A) goes below the liability (L), then the value of equity (E) will become zero since the bondholder takes all the value of the assets (Akhter & Hasan, 2015). This mechanism converts the equity into a call option with a long position where the face value of debt is the strike price. The call option will make a profit if the asset value goes over the liability or strike price (Akhter & Daly, 2017). The payoff equation is given below at equation 3.3.1.5.

$$E_T = \max(0, A_T - L) \qquad (3.3.1.5)$$

Using equation 3.3.1.2, the study creates a stochastic version of the balance sheet to derive the daily asset and liability value for a given time period T-t where the liabilities are discounted on a continuous basis with a risk free rate R_f, where N(d) in equation 3.3.1.2 represents the standard cumulative normal distribution function for d. Using the iterative process, the study can now create a structure of equations to derive the daily asset values (Löeffler & Posch, 2011). This process involves solving a system containing (T+1) equations for (T+1) unknown data. At this point, the study choose to compute a series of A_t covering 260 days, given most structural models are based on one-year default probabilities (Akhter & Daly, 2017). This is shown in equation 3.3.1.6 below:

$$A_t = \frac{[\, E_t - L_t e^{-r_t} N(d_2)]}{N(d_1)}, A_{t-1}$$

$$= \frac{[\, E_{t-1} - L_{t-1} e^{-r_{t-1}} N(d_2)]}{N(d_1)}, A_{t-260}$$

$$= \frac{[\, E_{t-260} - L_t e^{-r_{t-260}} N(d_2)]}{N(d_1)} \qquad (3.3.1.6)$$

At the beginning, the model guesses the asset value A_{t-a} where *a = 0, 1,2,3 ……260* and define the asset volatility (σ_A) as the standard deviation of log return from asset value (A_{t-a} multiplied by the square root of 260).The process start from base asset price, where asset equals to liability plus equity where liability (L) is the sum of deposits, short-term funds and half the long-term liabilities. The study use interpolation from two balance sheet dates to calculate the daily liability value of the firm, given most of the banks only communicate annual liability through their financial statements. All the data have been collected from Bankscope and

DataStream. The primary sample period is about 11 years, from 31 December 2004 to 31 December 2015. At this point, the study uses iteration (k = *1,2,3…….end)* to calculate d_1 and d_2 from equation 3.3.1.3 and 3.3.1.4. Then the study insert the values of d_1 and d_2 in equation 3.3.1.6 to obtain A_{t-a}. In the next step, using the A_t obtained from this process, the study calculates asset volatility (σ_A) for a moving window of 260 days. After that, using the asset values from the simulation and the daily index[8], the study calculates the daily excess asset return and daily excess index return by deducting the daily risk free return. It also calculates 260 days' time varying beta from these excess asset and index returns. At this point, the study calculates the expected daily asset return and drift rate from the previously calculated beta and risk-free rate using a capital asset pricing model (Merton, 1973).The study calculates DD using equation 3.3.1.1 starting from 2 January 2006 and continuing to 31 December 2015. Using the calculated DD values, it works out ΔDD (change in DD) over five days[9] using equation 3.1.1.7. This methodology gives 2606 daily observations for approximately 10 financial years for every bank in the sample (justification is given at subsection 3.2), starting from 6 January 2004 for the first part of this research.

$$\Delta DD_{i,t} = \frac{DD_{i,t} - DD_{i,t-5}}{|DD_{i,t-5}|} \qquad (3.3.1.7)$$

[8] A list of different stock indices and one-year government securities from DataStream is provided in Table 3.3.1.1.

[9] Past researchers reasoned that extreme financial events are more substantial in reducing noise if they are they are counted as a financial risk (5 days) rather than a financial day (Akhter & Daly, 2017)

Table 3.3.1.1- List of sample countries' stock indices and Risk free rates

Country	Risk free rate - 1 Year	Index
Australia	TR AUSTRALIA GVT BMK BID YLD 1Y (A$) - RED. YIELD	S&P/ASX 200 - PRICE INDEX
Belgium	TR BELGIUM GVT BMK BID YLD 1Y (E) - RED. YIELD	BEL 20 - PRICE INDEX
UK	TR UK T-BILLS BID YLD 12M (£) - RED. YIELD	FTSE 100 - PRICE INDEX
Switzerland	TR SWITZERLAND GVT BID YLD 1Y (SF) - RED. YIELD	SWISS MARKET (SMI) - PRICE INDEX
Sweden	TR SIDEN GVT BID YLD HIGH 1Y (SK) - RED. YIELD	OMX STOCKHOLM 30 (OMXS30) - PRICE INDEX
Spain	TR SPAIN GVT BMK BID YLD 1Y (E) - RED. YIELD	IBEX 35 - PRICE INDEX
South Africa	SA GVT BMK BID YLD 1Y (E) - RED. YIELD	FTSE/JSE ALL SHARE - PRICE INDEX
Netherland	TR NETHERLANDS GVT BID YLD 1Y (E) - RED. YIELD	NETHERLAND-DS Financials - PRICE INDEX
Mexico	TR MEXICO GVT BMK BID YLD 1Y (MP) - RED. YIELD	MEXICO IPC (BOLSA) - PRICE INDEX
Malaysia	TR MALAYSIA GVT BMK 1Y BID YLD (M$) - RED. YIELD	FTSE BURSA MALAYSIA KLCI - PRICE INDEX
Japan	TR JAPAN T-BILLS BID YLD 12M (Y) - RED. YIELD	TOPIX - PRICE INDEX
Italy	TR ITALY GVT BMK BID YLD 1Y (E) - RED. YIELD	FTSE MIB INDEX - PRICE INDEX
Germany	TR GERMANY T-BILLS BID YLD 12M (E) - RED. YIELD	DAX 30 PERFORMANCE - PRICE INDEX
France	TR FRANCE T-BILLS BID YLD	FRANCE CAC 40 - PRICE INDEX

	12M (E) - RED. YIELD	
Denmark	TR DENMARK T-BILLS BID YLD 12M (DK) - RED. YIELD	OMX COPENHAGEN (OMXC20) - PRICE INDEX
Brazil	BRAZIL GVT BMK BID YLD 1Y (E) - RED. YIELD	BRAZIL BOVESPA
US	TR US T-BILLS BID YLD 12M (U$) - RED. YIELD	NASDAQ 100 - PRICE INDEX
India	TR INDIA T-BILLS BID YLD 12M (IR) - RED. YIELD	NIFTY 500 - PRICE INDEX
China	TR CHINA T-BILLS BID YLD 12M (CH) - RED. YIELD	SHANGHAI SE A SHARE - PRICE INDEX
Korea	TR KOREA GVT BMK BID YLD 1Y (KW) - RED. YIELD	KOREA SE COMPOSITE (KOSPI) - PRICE INDEX

Following the calculation of the five-day change in DD, the study now moves to the calculation of exceedances within the distribution of ΔDD_i to convert them to country level for use as input variables of the multinomial logistic model (MLM). An extreme event or exceedance at time t for the i^{th} sample can be simply described as a value beyond the 90th percentile point on the negative tail of $\Delta DD_{i,t}$. For the first two parts of the thesis (intercountry and interstate contagion), the methodology counts the number of simultaneous co-exceedances at every bank in that specific country or state for each day and divide them into four discrete events – tranquil, disturbing, alarming and crisis, as discussed above (see Section 3.1). For the interbank contagion analysis, the thesis keeps the extreme events as they are for use as input variables. In the final state, the thesis uses these input or discrete events in a multinomial logistic model to predict the contagion risk.

3.3.2. Distance to inefficiency

Distance to inefficiency (DI) has its theoretical background in the credit risk structural models proposed by Merton (1974) and Leland (1994). They used DI as a quantitative measure of the firm's leverage affected by the volatility of the market estimation of its primary asset base (Leland, 1994; Merton, 1974). The DI shows us the probability of the firm's future insolvency and the distortions to stockholders' initiative if insolvency occurs (Atkeson, Eisfeldt, & Weill, 2013). To describe the operation of this counter-efficiency measure, one needs to start from the basic accounting equation. As per the previous section's discussion of distance to default, stochastic cash flow representation of asset and liability will be $A_t \; and \; L_t$. Theoretically, in a default scenario the liability of a firm will be above the current value of the assets, but in a perfect condition the current value of assets will be at least more than the value of liabilities $A_t \geq L_t$, where asset volatility (σ_A) represents the annualised standard deviation of asset value or the business risk of the firm. This scenario indicates that the leverage of a firm is the gap between the value of the asset and liability in a percentage scale ($\frac{A_t - L_t}{A_t}$) and the distance to inefficiency is the ratio of leverage to asset volatility at time t (as shown in equation 3.3.2.1).

$$\text{DI} = \left(\frac{A_t - L_t}{A_t}\right) * \frac{1}{\sigma_A} \qquad (3.3.2.1)$$

Following the procedure outlined in the previous section to calculate distance to default, the study computes the DI values from 2 January 2006 to 31 December 2015.The study also computes ΔDI over five days using equation 3.3.2.2. This procedure provides us with 2606 observations for approximately 10 financial years for all the sample banks.

$$\Delta DI_{i,t} = \frac{DI_{i,t} - DI_{i,t-5}}{|DI_{i,t-5}|} \qquad (3.3.2.2)$$

Repeating the procedure outlined in the previous section, the study methodology calculates the exceedances using the 90% threshold (following the DD procedure) within the distribution of ΔDI_i. Then, for the first two parts (intercountry and interstate contagion), the study count the number of simultaneous co-exceedances for each of the banks in that specific country or state for each day and divide them into four discrete events – tranquil, disturbing, alarming and crisis, as discussed above. For the interbank contagion analysis, the study keeps the extreme events as they are for use as input variables. In the final state, the study will use these input or discrete events in a multinomial logistic model to predict the contagion risk.

3.3.3. Distance to capital

Policymakers and financial institution regulators depend predominantly on popular market-based measures such as distance to default as the quantitative measurement of financial institutions' distance to risk (Blundell-Wignall & Roulet, 2013; Chan-Lau & Sy, 2007; Milne, 2014; Saldías, 2013), thanks to the effective marketable execution of Moody's KMV (Dwyer & Qu, 2007; Korablev & Dwyer, 2007). However, distance to default has limits when it comes to unqualified default risk measurement, because "the leverage pattern" differs from institution to institution (DeAngelo & Stulz, 2013, 2015). In the current framework of distance to default, the model assigns a higher risk score to the banks regardless of their built-in requirement for leverage. Furthermore, distance to default uses the bank's equity as financial buffer, which is less acceptable in modern scenarios (Guidara, Soumaré, & Tchana, 2013; Jokipii & Milne, 2008). Also in light of Prompt Corrective Action (PCA) and the Basel framework, everyone know that regulators and supervisors should intervene before the total exhaustion of the capital buffer (Kocherlakota & Shim, 2007; Mayes, Nieto, & Wall, 2008). Distance to capital (DC) is an improved framework that overcomes these limitations by using the relevant capital threshold in default risk calculations. In order to do that this research rearrange equation 3.3.1.1 using t=1 to derive equation 3.3.3.1.

$$DD_t = \frac{Ln\frac{A_t}{L} + \left(\mu - 0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \qquad (3.3.3.1)$$

where μ and σ are the drift rate and volatility for the underlying asset of the financial institution. According to equation 3.3.3.1, the default barrier for non-financial entities is the inability to make liability payments, where liability is the weighted average of short-term and long-term liabilities. In modern financial markets, a termination of financial establishment can materialise for reasons other than a deterioration of asset value past liabilities (Dabrowski, 2010; Moshirian, 2011). Rather than using the face value of liability as a default barrier, the study chose a new barrier more consistent with the current Basel and Prompt Corrective Action frameworks (Aggarwal & Jacques, 2001; Basel, 2010) and used by other contemporary studies of this field (Akhter & Daly, 2017). Equation 3.3.3.2 uses this new ideology to create a new generic distance risk formula:

$$DR_t = \frac{Ln\frac{A_t}{\lambda L} + \left(\mu - 0.5\sigma_A^2 \quad\right)T}{\sigma_A \sqrt{T}} \qquad (3.3.3.2)$$

where λ is a corrective feature that explains the difference triggers rooted in the Basel and PCA agenda (Liu, Papakirykos, & Yuan, 2004). From this understanding, the study can derive equation 3.3.3.3.

$$DR_t = \frac{\frac{A_t - \lambda T}{A_t}}{\sigma_A \sqrt{T}} \qquad (3.3.3.3)$$

In this case,

Bank Capital= Bank Equity = Asset – Liability > CAR x Asset

where CAR stands for capital adequacy ratio at a given time t. In this case, the study have used 8 percent from the Basel framework[10]. Therefore, one can define λ as:

$$\lambda = \frac{1}{1 - CAR_t} \qquad (3.3.3.4)$$

Now from equation 3.3.3.2 and 3.3.3.4 distance to capital will be:

$$DC_t = \frac{Ln\left(\frac{A_t}{\frac{1}{1-CAR_t}L}\right) + \left(\mu - 0.5\sigma_A^2 \quad\right)T}{\sigma_A \sqrt{T}} \qquad (3.3.3.5)$$

[10] From 2013, according to Basel III guidelines, a bank's tier 1 and tier 2 capitals must be at minimum 8% of its risk-weighted assets. This protection is designed to shape up banks' capital, which they could use in states of financial strain like global financial crisis of 2008/09.

Using equation 3.3.3.5, the study derives DC variables from 2 January 2006 to 31 December 2015. Then the study computes ΔDC over five days using equation 3.3.3.6. Just like DD, this procedure provides 2606 observations for approximately 10 financial years for all banks in the sample.

$$\Delta DC_{i,t} = \frac{DC_{i,t} - DC_{i,t-5}}{|DC_{i,t-5}|} \qquad (3.3.3.6)$$

Repeating the procedure outlined in the previous two sub-sections, the study now calculates the exceedances using a 90% threshold within the distribution of $\Delta DI_{i.}$ Then, for the first two parts of the research (intercountry and interstate contagion), the study counts the number of simultaneous co-exceedances across the banks in that specific country/state for each day and divide them into four discrete events – tranquil, disturbing, alarming and crisis. For the interbank contagion analysis (the third part of this research), the study keeps the extreme events as they are for use as input variables. In the final state, the study will use these input or discrete events in a multinomial logistic model to predict the contagion risk.

3.4 Multinomial Logistic Model

The multinomial logistic model is one of the most commonly used regression methods when it comes to assessing the probability of extreme shocks (Boyson, Stahel, & Stulz, 2010; Caggiano, Calice, & Leonida, 2014). Previous researchers have used the MLM method to quantify the likelihood of large changes in DD (Christiansen & Ranaldo, 2009; Gropp, Lo Duca, & Vesala, 2006).The thesis use

MLM in this research given this research has multiple discrete financial conditions. The MLM model considers one of the variables (first state) as the base product and calculates the likelihood of occurrence of the other three states given the base state. As the study adopt state 1 as the base, the likelihood of other variables at time t is demonstrated in equation 3.4.1, where x_t is stated as the row vector for y_t with β_m the coefficient vector.

$$P_{i,t} = \Pr(y_t = i) = \begin{cases} \frac{1}{1+\sum_1^3 \exp(x_t\beta_m)}, if\ i = 1 \\ \frac{\exp(x_t\beta_i)}{1+\sum_{m=1}^3 \exp(x_t\beta_m)}, if\ i < 4 \end{cases} \quad (3.4.1)$$

3.5 Explanatory Variables

As per the discussion above, the key explanatory variable in this research is the extreme shock in the distance to default, distance to inefficiency and distance to capital of the sample entities (the details of the model will be given on the next subsection). The percentage amount of exceedances in the sample bank, country or state's extreme shocks will give us a forecast of contagion risk within that sample. The thesis has included some other explanatory variables (MSCI global index, local stock market return volatility, development in real economy and time period for global financial crisis in the model for the first and second part of this thesis.

In order to calculate the global and local stock market volatility, the study takes five trading day weekly log returns from the underlying index. Then, using a GARCH (1,1) model, the study generates conditional variance as a proxy for stock index volatility. Equation 3.5.1 shows conditional GARCH volatility where X_t is the weekly return in time t with volatility of σ.

$$\sigma_t^2 = w + \alpha\varepsilon_{t-1}^2 + \beta\alpha_{t-1}^2 \qquad (3.5.1)$$

Using the same method described earlier in this chapter, the study defines the development in the real economy as five-day logarithmic change in the term structure spread as development in the real economy. The study then calculates the term structure spreads by taking the difference between the long-term (10 years) and short-term (5 years) interest rate. The difference between these rates indicate the difference between the time period yields. Equation 3.5.2 details this explanatory variable in time t.

$$\Delta yC_t = \frac{yC_t - yC_{t-5}}{|yC_{t-5}|} \qquad (3.5.2)$$

In the next subsection of the chapter is comprised of the research administrative requirements including different pillars of quality.

3.6 Research quality

According to previous researchers in this field, an acceptable research result is as acceptable as its inherent characteristic quality (Stenbacka, 2001). Diverse approaches to safeguard the quality of the result are recommended in any research. In this thesis, three different value procedures have been used to guarantee this. These instruments are described below.

3.6.1 Factor validity

Factor validity has been labelled as an important component of all present research. It has the aptitude to mark the difference amid reputable and pitiable works. Earlier academics note its standing given that a researcher's subjectivity can sway the elucidation of the outcomes (Gefen & Straub, 2005). In this thesis, factor validity is based on the investigator's all-encompassing (ten years) knowledge in the field of finance and proper research etiquette.

3.6.2. Internal validity

Internal validity can be described as the soundness of the study (research strategy, data collection, parameter exclusion etc.) and the certainty with which one can assert the results and conclusions (Mentzer & Flint, 1997). The internal validity of this research is assured primarily by the research methodology and data sources. In this regard, the study has created a firm research protocol to ensure a high standard of internal validity has been implemented throughout the methodology.

3.6.3. Reliability

Past researchers note that, in research, the conclusions must be more than a one-off finding – they should be repeatable (McKinnon, 1988). Further investigators must be capable of producing the same outcomes when performing the same investigation under identical circumstances (Evanschitzky, Baumgarth, Hubbard, & Armstrong, 2007). The use of rigorous research methodologies in this thesis ensures the core dependability of the study.

3.7. Conclusion

This chapter explained the methodologies used in this research project, describing the internal mechanisms of the core methodology, sample selection and composition, different distance to risk measures and the equations used to calculate them. It also discussed the multinomial regression model and descriptive statistics used in this thesis. The chapter, more generally, provided support for the specific quantitative research approaches used to address the research objectives of this thesis as elucidated in Chapter 1.

Chapter 4. Contagion risk in global banking sector

4.1. Introduction

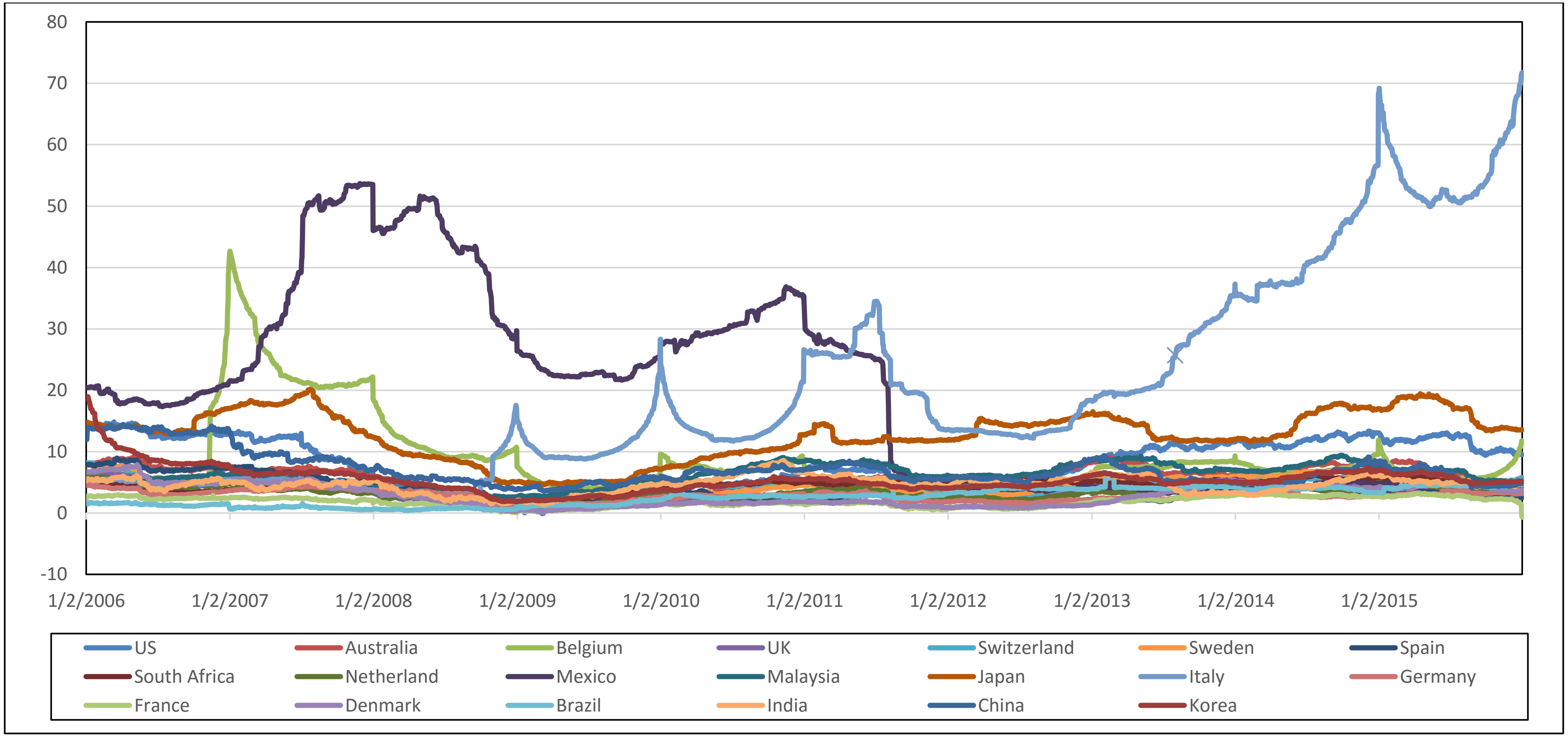
This chapter investigates contagion risk in the global banking environment using three different distance to risk measures (distance to default, distance to capital, distance to investment) as described in Chapter 3. The sample consists of 91 banks from 20 countries, including all G8 and BRICS countries. The chapter models extreme shocks for the top banks in a specific country as a function of extreme shocks experienced by other banks in country-level settings using four discrete conditions or financial states. The study then calculates the probability of these shocks moving through one country's banking system to another's by employing a multinomial logistic model. Overall, the study finds evidence of strong correlation between most of the sample countries' banking systems and the UK and US. Other countries have a moderate effect on each other in terms of shock transfer. The results also indicate that less developed or developing economies less vulnerable to financial shocks. The findings also suggest a greater need for cross-border supervision among banks across the globe.

The following discussion reports the results in terms of distance to default (Section 4.2), distance to inefficiency (4.3) and distance to capital (4.4) value calculation. It then describes the findings from the exceedances calculation (4.5). Finally, in Section 4.6, the study describes the results of the contagion risk analysis of the chapter's model.

4.2. Distance to default (DD) calculation

Figure 4.1 illustrates the movement plot of distance to default (DD) for the sample countries. This chapter has calculated these distance to default values using the methodology described in Chapter 3 (sub-section 3.3.1). Given the enormous volume of the raw daily bank-level DD data, figure 4.2.1 plots the data for every country rather than every bank in the figure using simple arithmetic mean. This is just to help the readers to visualise the data, for the MLM model the study uses all the calculated DD. In general, the DDs tend to stay near the median of the distribution. This figure illustrates that most of the DDs for the 20 countries are stacked in between 0 to 10 (where 1 is one standard deviation from the median). It can also be observed that DDs decreased slightly in the period 2008–2010, during the global financial crisis. However, two countries show an exception to this general trend, namely Mexico and Italy. Historically, Italian banks have outperformed the global leaders, mostly based on the innovative nature of the Italian economy, which includes a large number of global luxury brands (DeBresson, Sirilli, Hu, & Luk, 1994). However, during the GFC there was a sharp decline in their performance given the Italian government was unable to bail the banks out (Adler-Nissen, 2017; Fourcade, 2013). After the critical period of the GFC, however, the Italian banks' DD values in recovered strongly (as indicated in the figure) and are currently positioned well ahead of other countries. Mexico, prior to the GFC, was in an economically advantageous position in virtue of its geographic proximity to the US. This changed dramatically after the GFC, a trend attributed to investor hesitation in some provinces of Mexico and a dramatic drop in foreign direct investment after the GFC (Hanson, 2010).

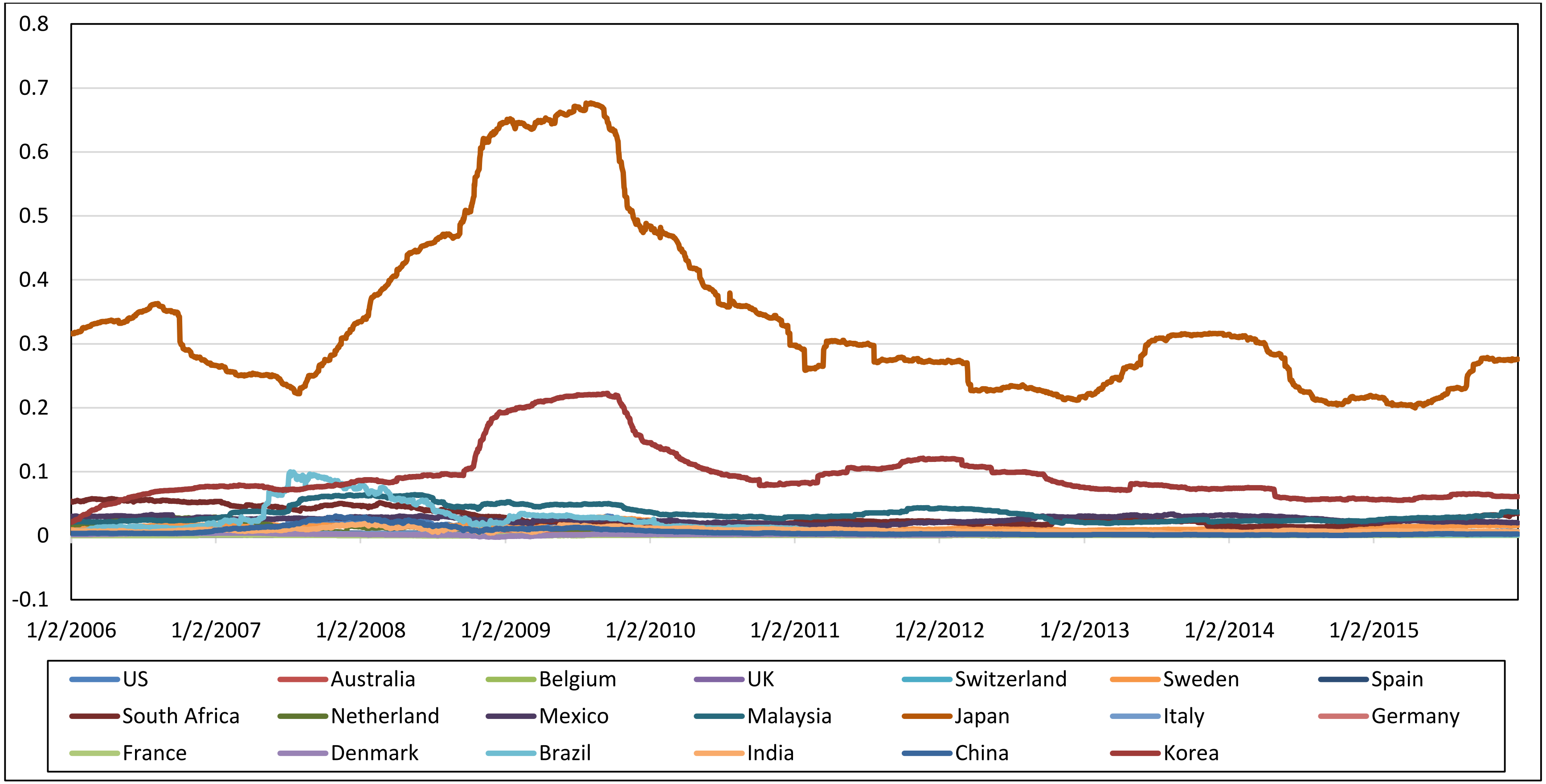
Figure 4.2.1. Distance to Default Values



4.3. Distance to inefficiency (DI) calculation

Figure 4.3.1 illustrates the movement of distance to inefficiency (DI) for the sample countries. The chapter has calculated these distance to inefficiency values using the methodology described in Chapter 3 (sub-section 3.3.2). Most DIs are confined to a range between 0 to 0.06 (where each unit represent one standard deviation from the mean). The chart follows a similar pattern to the distance to default diagram (Figure 4.2.1). However, it can be clearly seen that the DIs are very closely stacked (compared to DDs), which indicates that, for practical purposes, most banks' distance to inefficiency is about the same. The most interesting feature of the figure is the stability over the last 10 years, including the GFC. However, the distance to inefficiency plots for Japan and Korea exhibit a different trend. Their distances to inefficiency were plotted above the global median throughout the sample, and the distance accelerates during the GFC (2008–2010). This trend can be attributed to the banking practices of these Asian countries, which historically focus more on financial efficiency (Drake & Hall, 2003; Park & Weber, 2006).

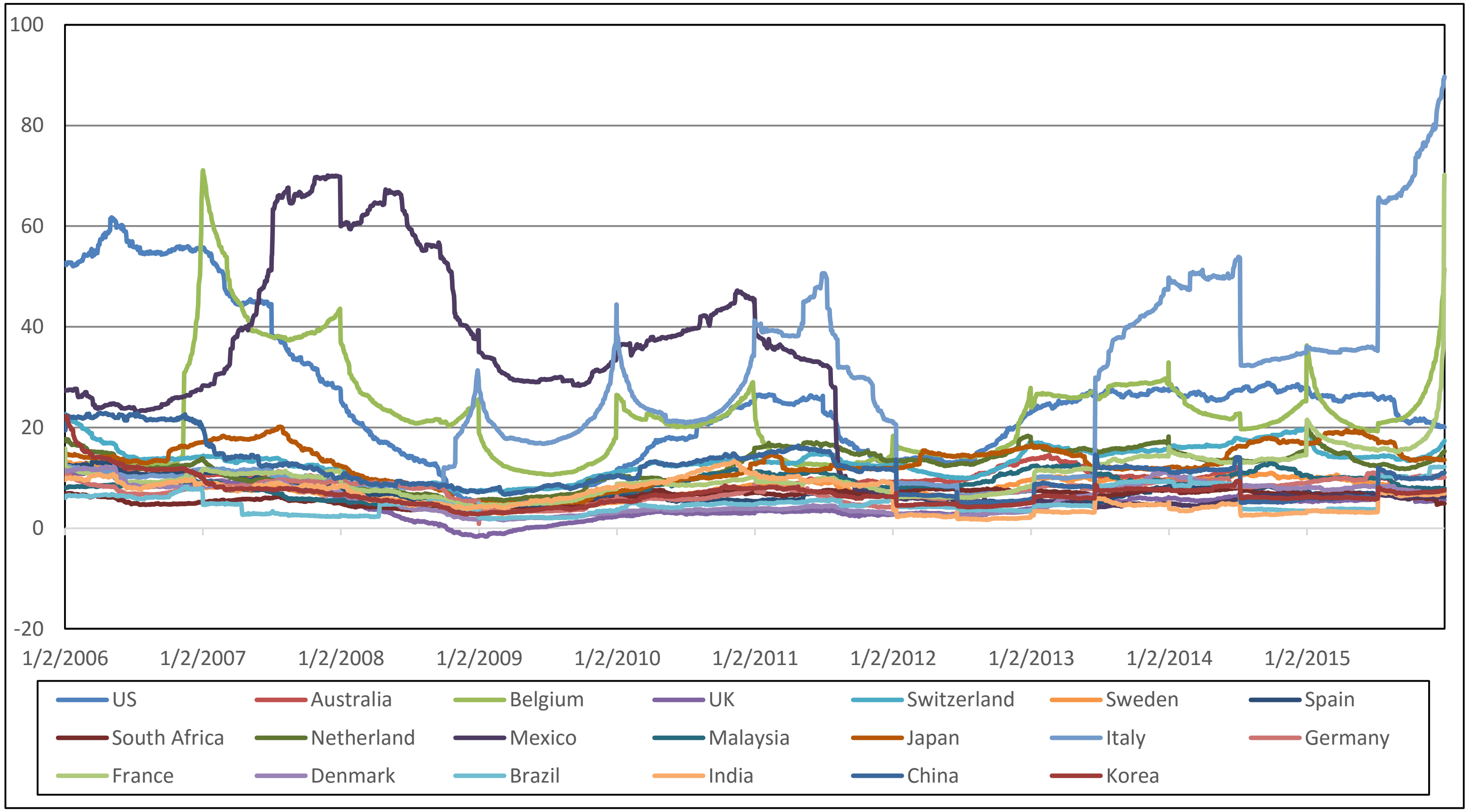
Figure 4.3.1 Distance to Inefficiency Values



4.4. Distance to capital (DC) calculation

Figure 4.4.1 illustrates the calculated value of distance to capital (DC) for the sample countries. Most of the countries' DCs are plotted between 0 and 20, which indicates a high degree of volatility in this distance measure, and therefore a highly volatile international banking system. Mexico, the US and Italy showed the same pattern as in the DD and DI measures. However, Belgium – the site of one of the safest and best-connected financial centres in the world – enjoys a higher capital value protection (Van Overfelt, Annaert, De Ceuster, & Deloof, 2009). There are two 'drop zones' in the distance to inefficiency graphs where values declined significantly: the period of the global financial crisis (circa 2008–2009) and a two-year period from 2011 to 2013.

Figure 4.4.1 Distance to Capital Values



4.5. Exceedances Calculation

In this step, the study calculates the exceedances (or co-exceedances) from the previously calculated distance to risk measurements (distance to default, distance to inefficiency and distance to capital). These exceedances are used as input variables for the multinomial logistic regression model. As explained in Chapter 3, an extreme event or exceedance at time *t* for the i^{th} sample can be simply described as a value beyond the 90th percentile point on the negative tail of the change in the distance to risk measures, e.g. $\Delta DD_{i,t}$. The results from the exceedances calculation show some interesting patterns. For most of the sample countries, distance to inefficiency and distance to default are more stable in lower state conditions (1 and 2). On the other hand, distance to capital is increases volatility at a higher rate than the other measures, moving into states 3 and 4 in the highest percentage. The upward trend in volatility increases for most sample countries over two periods, 2008–2009 and 2012–2013). The distance risk measures for the US, India and China never reach state 4, while the European Union countries tend to move into states 3 and 4 more frequently than other countries. Overall, it appears North American and Asian countries' distance risk measures tend to stay with the range of states 1 and 2 for all the distance measures. The results, at this stage, indicate that for all practical purposes the North American and Asian banks tend to be less prone to systemic risk than their European counterparts.

4.6. Contagion risk result

4.6.1. Distance to default contagion

The distance to default contagion (shock transfer) results show a strong correlation between the sample countries. The results identify contagion using the one-day lagged exceedances in the other nineteen countries if their Multinomial Logistic Model regression results are positive and substantial. The model assumes this as a contagion commencing in that country and moving into the dependent variable or host country in accordance to the thesis's methodology from Chapter 3. Tables 4.6.1.1 to 4.6.1.3 illustrate the shock transfer results for all the countries using this methodology. In order to explain them in a simplified manner, the study illustrates the p-value (using 5% confidence level)[11] for different states excluding the base state 1[12] in tables 4.6.1.1 to 4.6.1.3. In these tables, the model also includes stock market volatility, world index volatility, the GFC and term structure spread as explanatory variables, following the practice of previous studies (Chan-Lau & Sy, 2007; Daly, Batten, Mishra, & Choudhury, 2017).

These results clearly show strong support for the autocorrelation of the exceedances, given most of the exceedances are positively significant for the sample countries.

[11] The study discovers that the contagion effect is most substantial at the five per cent level for reporting the coexceedances in the thesis'smodel. This is also supported by increased Pseudo R Square in the thesis'sestimate outcome. It is also significant that adding the one-day lagged exceedances from other sample countries does not affect the majority of fluctuations in results compared to two- or three-day lagged variables.

[12] In a multinomial logic model, the model takes the first state as the base outcome and computes the possibility of other states occurring given the base state. Thus the result of the base state is omitted (Matejka & McKay, 2014).

Beyond that, there is clear evidence of a correlated global banking sector (shown by the p values from the tables) with some major patterns. As expected, the US is the most influential factor, closely followed by Mexico, France, World index, GARCH volatility and the GFC. The results also show clear patterns of shocks moving between economies with a one-day lag, consistent with the thesis'smethodology. An unexpected result, however, is the lack of shock transfer for the rest of the G-8 economies. This clearly suggests that these leading global economies, such as the UK and Germany, are not connected to other economies at a level that was expected (Wong & Fong, 2011). The US, Spain, South Africa, India and China are least effected by other countries' financial conditions accordance to these results. Of these five countries, South Africa, India and China are currently the key members of BRICS group, which make it reasonable to assume that, as developing economies, they still have not achieved same level of interconnectivity as developed nations. However, the fact that the US and Spain have shielded their economies from the external shocks of other economies is quite remarkable, especially as the US is the most influential economy when it comes to transmitting shocks. This indicates the extent to which the world economies are dependent on the US, but not vice-versa. In addition, Switzerland, Sweden, Mexico and Denmark transfer shocks from a large number of economies.

Table 4.6.1.1. DD state 2 Contagion

	US	Australia	Belgium	UK	Switzerland	Sweden	Spain	South Africa	Netherland	Mexico	Malaysia	Japan	Italy	Germany	France	Denmark	Brazil	India	China	Korea
Lag number of exceedances: US		0.037	0.003	0.014	0.021	0.02			0.017		0.019					0.008		0.011		
Lag number of exceedances: AU														0.025						
Lag number of exceedances: BE	0.019				0.013											0.005				
Lag number of exceedances: UK						0.049														
Lag number of exceedances: SL											0.031									0.017
Lag number of exceedances: SW																0.025				
Lag number of exceedances: SP								0.044	0.001			0.003			0.005					
Lag number of exceedances: SA		0							0.007										0.003	
Lag number of exceedances: NL																				0.003
Lag number of exceedances: MX				0.007	0.006	0.006								0.018	0					
Lag number of exceedances: MY		0.01												0.04					0.015	
Lag number of exceedances: JP										0.029										0.035
Lag number of exceedances: IT			0.03		0.035					0.025	0.017			0.022		0.028				
Lag number of exceedances: GM										0.035										
Lag number of exceedances: FR	0.005					0.005								0.019					0.002	0.028
Lag number of exceedances: DM																				
Lag number of exceedances: BR			0.015	0.01	0.031															
Lag number of exceedances: IN																				0.022
Lag number of exceedances: CH																0.044				
Lag number of exceedances: KR																				
Garch Volatility		0.003											0.005		0.024			0.049		
World index volatility													0.025							
Term Structure									0.006											
Constant																				
GFC	0	0.034	0.002	0.027		0.016	0.03			0.039						0				0.043

Table 4.6.1.2. DD state 3 Contagion

	US	Australia	Belgium	UK	Switzerland	Sweden	Spain	South Africa	Netherland	Mexico	Malaysia	Japan	Italy	Germany	France	Denmark	Brazil	India	China	Korea
Lag number of exceedances: US		0.012	0	0	0				0.017	0.027	0		0.046			0.014		0.006		
Lag number of exceedances: AU																0.005				
Lag number of exceedances: BE																0.032	0.023			
Lag number of exceedances: UK						0.009		0.01									0.023			
Lag number of exceedances: SL																0.009				
Lag number of exceedances: SW										0.009										0.004
Lag number of exceedances: SP								0.018												
Lag number of exceedances: SA		0.015								0.037						0.021				
Lag number of exceedances: NL													0.006	0.001						
Lag number of exceedances: MX	0.004	0.042		0.021	0.045	0.027									0.037					
Lag number of exceedances: MY		0.035												0.034						0.011
Lag number of exceedances: JP			0.044						0.003											0.005
Lag number of exceedances: IT																				
Lag number of exceedances: GM										0.011								0.032		
Lag number of exceedances: FR					0.006	0.005						0.025	0.03	0.013		0.007	0.042		0.014	0.001
Lag number of exceedances: DM																				
Lag number of exceedances: BR			0.015					0.002							0.001					
Lag number of exceedances: IN																				
Lag number of exceedances: CH	0.019																	0.01		0.035
Lag number of exceedances: KR				0.012																
Garch Volatility		0.008									0.017	0.007								
World index volatility						0.031							0.033		0.049					
Term Structure								0.015	0.009					0.014		0.021				
Constant																				
GFC	0.001	0.022								0.044										

Table 4.6.1.3. DD state 4 Contagion

	US	Australia	Belgium	UK	Switzerland	Sweden	Spain	South Africa	Netherland	Mexico	Malaysia	Japan	Italy	Germany	France	Denmark	Brazil	India	China	Korea
Lag number of exceedances: US		0		0	0.043								0.044			0.008	0.023			0.004
Lag number of exceedances: AU						0.037														
Lag number of exceedances: BE																				
Lag number of exceedances: UK																				
Lag number of exceedances: SL																	0.001			
Lag number of exceedances: SW																				
Lag number of exceedances: SP			0.003																	
Lag number of exceedances: SA												0								0.002
Lag number of exceedances: NL																0.039				
Lag number of exceedances: MX		0.02			0	0.001								0.016						
Lag number of exceedances: MY																0.03				
Lag number of exceedances: JP					0.004				0.011											0.013
Lag number of exceedances: IT																				
Lag number of exceedances: GM																				
Lag number of exceedances: FR							0.033					0.019								0
Lag number of exceedances: DM																				
Lag number of exceedances: BR																				
Lag number of exceedances: IN									0.018	0.044										
Lag number of exceedances: CH									0.047						0.023		0.032			
Lag number of exceedances: KR		0.001																		
Garch Volatility		0.003			0.017					0.03	0.002	0.004					0.031			0
World index volatility			0.028			0.001					0.028									
Term Structure																	0.016			
Constant																				
GFC		0.008	0.043	0												0.031				

The significant p-values from tables 4.6.1.1 to 4.6.1.3 are collated in table 4.6.1.4. In this table, one can see an overall macro-economic pattern between the countries. Less developed countries are more immune to external shocks from their counterparts and vice versa. Additionally, the higher the level of the shock the lower their movement throughout the economies. Among the other explanatory variables, the GFC played a major role as an explanatory variable, whereas others failed to demonstrate significance in the model.

Table 4.6.1.4. DD Contagion

	US	Australia	Belgium	UK	Switzerland	Sweden	Spain	South Africa	Netherland	Mexico	Malaysia	Japan	Italy	Germany	France	Denmark	Brazil	India	China	Korea
Lag number of exceedances: US		234	23	234	23	2			23	3	23		34			234	4	23		4
Lag number of exceedances: AU						4								2		3				
Lag number of exceedances: BE	2				2					2						23	3			
Lag number of exceedances: UK						23		3									3			
Lag number of exceedances: SL						2					2					3	4			2
Lag number of exceedances: SW										3						2				3
Lag number of exceedances: SP			4					23	2			2			2					
Lag number of exceedances: SA		23							2	3						3			2	4
Lag number of exceedances: NL													3	3		34				2
Lag number of exceedances: MX	3	34		23	23	234					4			24	23					
Lag number of exceedances: MY		23												23		4			2	3
Lag number of exceedances: JP			3		4				34	2										234
Lag number of exceedances: IT			2		2					2	2			2		2				
Lag number of exceedances: GM						2				23								3		
Lag number of exceedances: FR	2				3	3	4					34	3	23		3			23	234
Lag number of exceedances: DM				24																
Lag number of exceedances: BR			23	2	2			3							3					
Lag number of exceedances: IN									4	4										2
Lag number of exceedances: CH	3								4						4	2	4	3		3
Lag number of exceedances: KR		34		3			2													
Garch Volatility		4			4					4	34	34	2		2		4	2		4
World index volatility			4			34					4		23		3					
Term Structure				4		3		3	23					3		3	4			
Constant																				
GFC	2	234	4	234		2	2			23						24				

4.6.2. Distance to inefficiency contagion

Distance to inefficiency values show a similar pattern of shock transfer as distance to default (see previous section). Table 4.6.2.1 shows the overall shock transfer result for the sample countries for this contagion risk. Overall, the result shows a strong correlation between countries. The chapter uses one-day lagged exceedances as contagion for each of the 20 sample countries as the explanatory variables of other countries. The study also include stock market volatility, world index volatility, the GFC and term structure spread as explanatory variables.

Other than the clear evidence of a highly correlated global banking sector (for most of the countries), the results show some major patterns of shock movement following the path of DD in the previous part. Again, the distance to inefficiency indicator from the US identifies that country as the global leader, being most influential variable in the sample followed by distance to inefficiency in the UK, distance to inefficiency in Germany, stock market volatility and the GFC (as expected). Relating the result with the previous section, DI shows more interconnectedness among economies other than Belgium, Japan, Brazil and India, where shock from other countries was not transmitted to their financial sector. Most surprisingly, India is immune from the shocks from other economies. The study attributes this trend to the underlying characteristics of the Indian economy, which depends largely on non-financial business (Bosworth, Collins, & Virmani, 2007). Among the other explanatory variables, the GFC was most significant whereas, once again, other explanatory variables failed to exert a significant influence within the model. Overall, the general patterns are quite similar to the distance to default. Again, less developed countries are more immune to external shocks and smaller shocks travel more than larger shocks.

Table 4.6.2.1- DI Contagion

	US	Australia	Belgium	UK	Switzerland	Sweden	Spain	South Africa	Netherland	Mexico	Malaysia	Japan	Italy	Germany	France	Denmark	Brazil	India	China	Korea
Lag number of exceedances: US		234	234	234	234	234	234		4	23	4		3	4	34	2				
Lag number of exceedances: AU			24		4	3									24					
Lag number of exceedances: BE		23			2	3			3	4	4					4				
Lag number of exceedances: UK	23	3				2		3				3		23	34		2			
Lag number of exceedances: SL				4												4			2	3
Lag number of exceedances: SW				34										2	4	2				
Lag number of exceedances: SP		34									2		234							
Lag number of exceedances: SA										34	3					2			3	3
Lag number of exceedances: NL				4				3			2		24							
Lag number of exceedances: MX	3	2														3			23	
Lag number of exceedances: MY				23	234	4				3			3							
Lag number of exceedances: JP	2														4					4
Lag number of exceedances: IT							234	4	3										2	
Lag number of exceedances: GM		3	3	234			2	2	2	3			4		24				3	
Lag number of exceedances: FR																3				
Lag number of exceedances: DM	2				3	3														
Lag number of exceedances: BR		4						34		3				3						
Lag number of exceedances: IN					2															
Lag number of exceedances: CH		4					2			2							2			
Lag number of exceedances: KR							3		3			23							2	
Garch Volatility	3	34		2		234	24		23		234		2	2	24					4
World index volatility				3	4	24			234				2		24					
Term Structure	2	4	2			3					4			23			3			
Constant																				
GFC	23	234		234	23	234	2	3	234					2	3	234	2		3	2

4.6.3. Distance to capital contagion

The distance to capital result displays a pattern of shock transfer analogous to the results of the previous two distance measures. Table 4.6.3.1 shows the overall shock transfer results for the DCs. Overall, the result shows a robust correlation between the world's economies. As before, the chapter includes one-day lagged exceedances as contagion for each of the 20 sample countries as the explanatory variables of other countries. The chapter also includes stock market volatility, world index volatility, the GFC and term structure spread as explanatory variables.

The US appears to be the most influential economy at transferring shocks, followed by the UK and Japan. Table 4.6.3.2 also illustrates that Brazil, China and South Africa are immune from the extreme shocks transmitted by other countries. This supports the thesis's previous findings that less developed countries are more immune to external shocks. However, Australia, the Netherlands, France and Korea are most affected by other economies' extreme shocks according to these results. The distance to capital follows a similar pattern to DD and DI. The GFC has a significant impact on DC. Less developed countries are more immune to outside shocks and smaller shocks move faster than larger shocks.

Table 4.6.3.1. DC Contagion

	US	Australia	Belgium	UK	Switzerland	Sweden	Spain	South Africa	Netherland	Mexico	Malaysia	Japan	Italy	Germany	France	Denmark	Brazil	India	China	Korea
Lag number of exceedances: US		4	234	34	34	234	2		23	3	3	3	24			234		2		4
Lag number of exceedances: AU			4			4				3			3	2				2		
Lag number of exceedances: BE		3			2					4					2			2		
Lag number of exceedances: UK	3	234			234		4	34		2				4	3	3	3	23		4
Lag number of exceedances: SL		23	4	2																2
Lag number of exceedances: SW	23				2					3	4	2						23		23
Lag number of exceedances: SP									2			2								24
Lag number of exceedances: SA					2					3		34								4
Lag number of exceedances: NL														3	2			23	23	2
Lag number of exceedances: MX	3			3	3	24	2				4			234	23					
Lag number of exceedances: MY		4												3	2					
Lag number of exceedances: JP		3	34	23	4				34				4	24	34	3				234
Lag number of exceedances: IT		4	2		2				4			24		2					3	
Lag number of exceedances: GM						4	34		4	34			234		4					
Lag number of exceedances: FR		34			23	23	4											3		4
Lag number of exceedances: DM			4												4					
Lag number of exceedances: BR								3	4				3							
Lag number of exceedances: IN	3	3						3	23	4			3		2				2	
Lag number of exceedances: CH				24					2			23								3
Lag number of exceedances: KR		4	4				2									4		3		
Garch Volatility	3				34					4	34	3	2		2		4		23	34
World index volatility		4				4					4				23					
Term Structure		4					4	3	4				23	2		3	4			
Constant																				
GFC	23			34	2		2		23			4		2				3	2	

4.6.4. Overall contagion

Finally, putting all three sets of results together will provide a clear picture of international contagion in the global banking sector. As expected, the developed countries are more affected than the developing countries when it comes to transmitting extreme shocks. Among the developed economies, the UK and the US are the two dominant economies when it comes to spreading shockwaves throughout the global banking sector. The results also clearly demonstrate that whenever a banking meltdown happens in these economies (US and UK), it is transmitted to most countries around the globe. The global financial crisis and the volatility of stock returns also had a dominant role in contagion risk in banking sector. The results indicate that developing economies and BRICS countries, such as Brazil, India and Malaysia, are the least affected by negative market movement or extreme state shock transfer. However, European countries are more prone to shock transfer, i.e. Switzerland, the Netherlands, France and Denmark. On the other side of the globe, Australia is the only extreme case where an economy receives most of the shocks from other economies but fails to transmit their shock to other countries; this is more commonly a characteristic of less developed economies. The chapter concludes that this is due to the more conservative nature of the Australian financial sector (Davis, 2011).

4.7. Conclusion

This chapter investigated the contagion risk for the global banking environment using three different distance to risk measures. Extreme shocks for global top banks were modelled as a function of extreme shocks experienced by other banks in country level settings. Four separate conditions of financial states (tranquil, disturbing, alarming and crisis) were used in this regard. The probability of these states moving through one country's economy to another was calculated using the multinomial logistical model.

Overall, the findings using all three different distance to risk measures revealed strong correlation between the sample countries' banking systems and the UK and US. Other countries' banking systems have a moderate effect on each other when it comes to shock transfer. The results also indicate that less developed or developing economies' banking systems more resistant to financial shock. The key challenge is to ensure adequate collaboration related to cross-border supervision among banks at the global level. These changes need to be created and implemented by global regulators in collaboration with their local counterparts. This will not only be beneficial to the financial institutions but will also significantly benefit all the stakeholders involved in the process.

Chapter 5. Local contagion risk in US banking

5.1. Introduction

This chapter investigates contagion risk between US states using the three different distance to risk measures (distance to default, distance to capital, distance to investment) described in the methodology. The chapter looks into US interstate contagion because of the enormous impact of the US economy on the global level. Most of the US states have greater economic capacity than many small- to medium-sized countries (see Figure 5.1.1). Here the chapter has examined the contagion risk from 15 US states to the other US states (of the chapter's sample) and to 19 economically important countries (from the previous chapter) using extreme shocks as a quantifiable instrument of systemic risk. In order to do so, the study has measured the systemic risk using three altered version of distance to risk methods (distance to default, distance to inefficiency and distance to capital) introduced by the option pricing theory (Merton, 1976). As like the previous chapter, this chapter models extreme shocks for each US state as a function of extreme shocks experienced by other US states (in the sample) and countries using four separate financial conditions. The chapter then finds the probability of these financial states moving from one state's banking system to another state's banking system or another country's banking system by employing the multinomial logistical model. The results of this chapter illustrate a robust correlation between the sample US states' and countries' banking systems; thus, shock from one state or country affects the other US states and countirs in the sample within a one-day lag. The study has also observed that smaller states transmit and receive more value shocks than their larger counterparts, while larger states show a higher capacity to resist shock than their smaller counterparts in all DD, DI and DC spillovers.

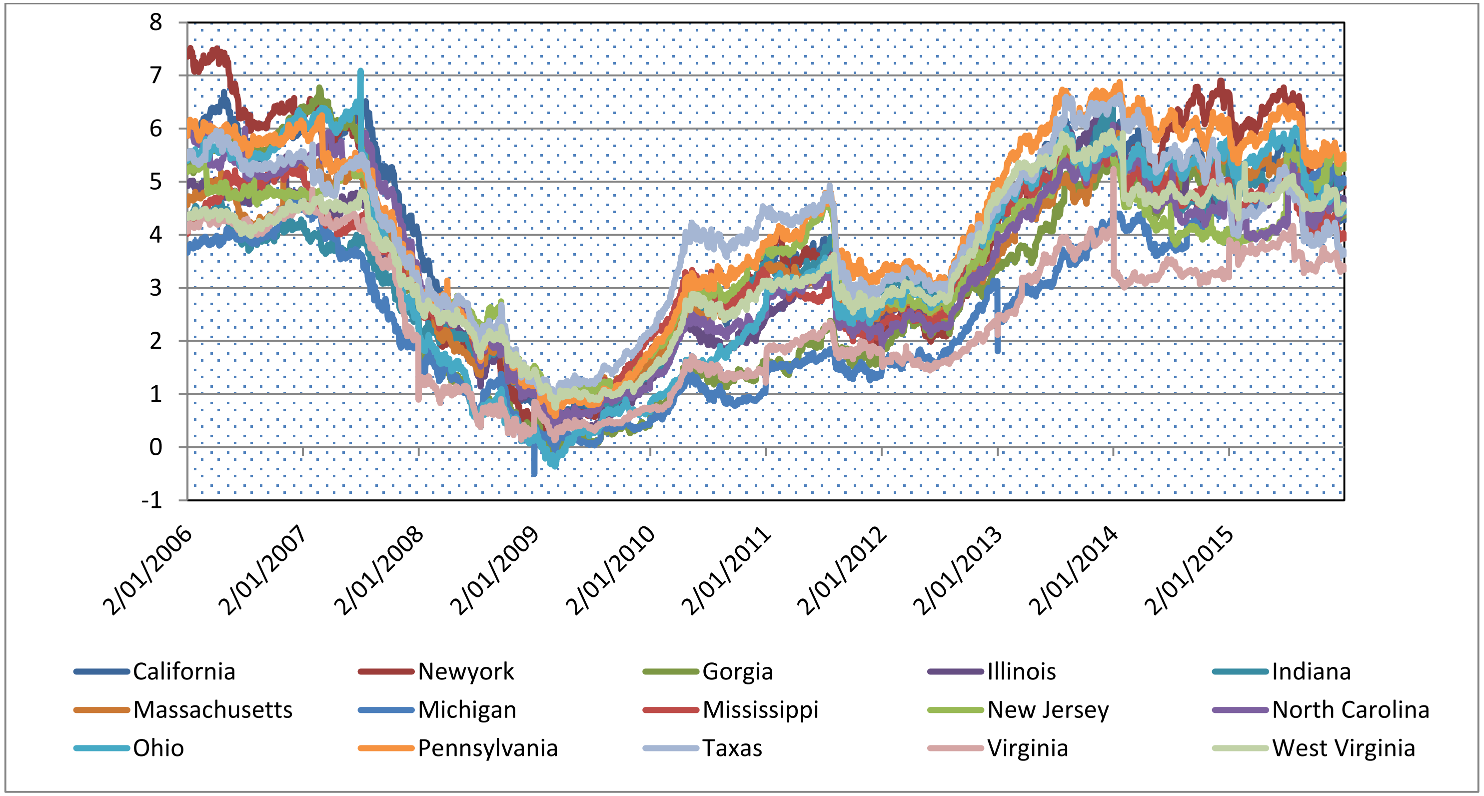
In the coming subsections, the chapter outlines the results of distance to default (Section 5.2), distance to inefficiency (5.3) and distance to capital (5.4) value calculations. The study then uses the exceedances calculation (5.5) as input variables of the core model. Finally, (5.6), the study discusses the results of the contagion risk.

Figure 5.1.1 Size of US states' economies

5.2. Distance to default calculation

Figures 4.2.1 and 5.2.1 represents the graphical movement plot for the thesis's calculated DDs. Rather than putting all of them together; they are represented in two different plots. In the first plot is for the DDs for all the US states, and the second one is for the DDs for all the sample countries used in this chapter. The first figure shows that US states follow the exact same pattern throughout the graph. They start on average around 5 at the beginning of 2006 then go down to 1 at the end of 2009 (the higher the DD value the better for the banks given it is more distant than the hypothetical inefficient point), which is understandable as this is the period of the global financial crisis (2008-10). Finally, they start to recover at the end of 2010 and have been positioned steadily around 5 from the end of 2015. They also show a slight drop period at the end of 2012, reflecting a wider slowdown in the global economy (Shin, 2014). This shared pattern indicates that US state economies are heavily correlated and tend to follow each other. This correlation pattern indicates a high risk for contagion among the US states. On the other hand, the DD chart for sample countries (Figure 4.2.1) shows a more diverse result; the DDs from different countries follow a similar pattern but with a high interval bracket compare to the US states. The DD values in this chart (5.2.1) are stacked between 0 and 10. While the common pattern exhibits an average of around 5, deceasing over the period of the GFC, two countries – Mexico and Italy – demonstrate some immunity to this overall trend. As noted earlier (see Section 4.2), Italian banks traditionally exceed the global mean based on the innovative nature of the Italian economy. There was a sharp deterioration at the time of the GFC, but Italian banks have since improved greatly and are presently placed way ahead of other countries (as shown in Figure 4.2.1). Again as noted in Section 4.2, prior to the global financial crisis Mexico was in a strong position due to its links to US, but was impacted by the crisis of 2009-2010 and went down which also reflects investor reluctance and falls in foreign direct venture after global financial crisis (Hanson, 2010).

Figure 5.2.1 Distance to default values for US states[13]

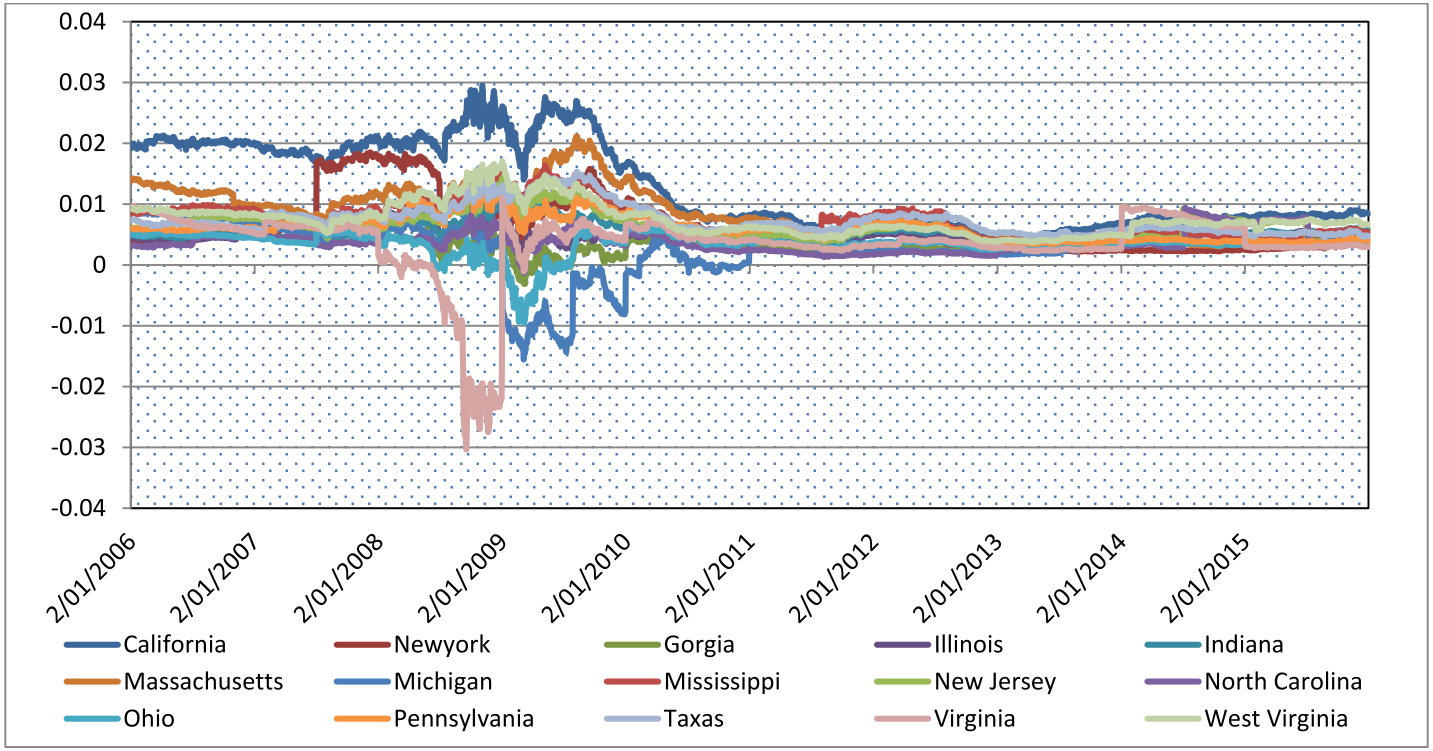


[13] Vertical axis represents the distance from the hypothetical default point where each unit is represented by one standard deviation from the mean. According to the thesis'smethodology higher the distance better for the banks.

5.3. Distance to inefficiency calculation

Figures 5.3.1 and 4.3.1 represent the distance to inefficiency values for the sample US states and countries as like DD. The first (Figure 5.3.1) shows the distribution of the DIs of US states. From the first chart, it can be seen that these state economies are highly correlated and tend to move together, as in the previous results from distance to default. They range between 0 and 0.01 of the DI scale, other than during the time of the global financial crisis. In the year 2009-2010, the DIs of US states become highly volatile and scatter both ways around the mean. An important observation about the state DIs is that, even in the times of greater financial distress (e.g. 2009), the average mean value is always the same. Four sates stayed below 0 in the GFC period – Virginia, Michigan, Ohio and Georgia. A special case in the chart is California; before the GFC, was always considerably ahead of the other states, but after that period stacked with the others. The next graph (5.3.1) shows the DI distribution for the sample countries. Compared to the US states, they are slightly more scattered, with values ranging between 0 and 0.06. The exceptions are Japan and Korea, whose DIs are plotted above the comprehensive average all through the ten-year period, and especially during the GFC period. This pattern can be credited to the different banking practices of these Asian countries where they focus on extreme efficiency (Drake & Hall, 2003; Park & Weber, 2006). The overall findings of the section indicate that, due to the extreme similarities of the distance to inefficiency values across the world, for practical purposes DIs will mostly remain the same in future.

Figure 5.3.1. Distance to inefficiency values for US states[14]

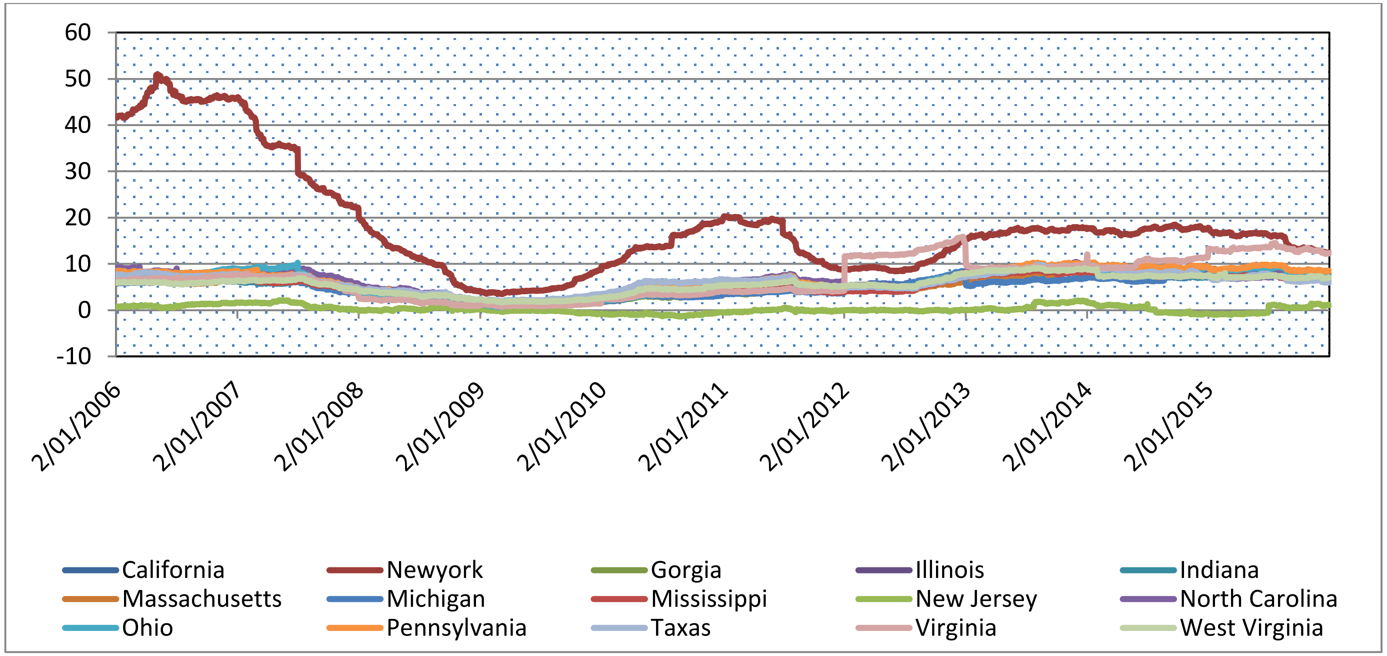


[14] Vertical axis represents the distance from the hypothetical inefficient point where each unit is represented by one standard deviation from the mean. According to the thesis'smethodology higher the distance better it is for the banks.

5.4. Distance to capital calculation

Following Chapter 3, Figure 5.4.1 and Figure 4.4.1 illustrate the distance to capital values for the sample US states and countries respectively. The first chart represents the state level DCs which follow a similar pattern to DD and DI and move together. They are always plotted between 5 and 10, with the exception of two states and during the GFC period. In 2008–09 they went back up to 0 but subsequently recovered gradually. The two exceptions in the first chart are New York and New Jersey. New York, being the financial capital of the world (Sassen, 2016), was always positioned higher (at times up to 10 times higher) than the mean value before the global financial crisis. After 2010 it exhibited rapid decline, but still managed to stay significantly higher than any other state throughout the sample time period. On the other hand, New Jersey was always lower other states; at the peak of the global financial crisis, it even experienced negative scores on the distance to capital scale. It remained between around 0 and 1 through the timetable in accordance with the calculation. This occurrence may come from the highly global dependent characteristics of New Jersey economy (Matzler, Veider, & Kathan, 2015). The next chart (country-level DCs) depicts a more correlated world economy, but certainly not as closely correlated as the US states. Maximum distance to capital values are situated between 0 and 20, clear proof of the increased volatility in this distance measure. Mexico and Italy's DI follow the same pattern as the DD in the previous section. The result also shows that Belgium enjoys higher capital value security, a finding also supported by previous researchers (Van Overfelt et al., 2009). Again following the trend of distance to default, there are two drop zones in the DI chart where the scores deteriorated considerably, the global financial crisis and a two-year period from 2011 to 2013.

Figure 5.4.1. Distance to capital values for US states[15]



[15] Vertical axis represents the distance from the hypothetical capital default point where each unit is represented by one standard deviation from the mean. According to the thesis's methodology, the higher the distance the better it is for the banks.

5.5. Exceedances Calculation

In this phase, the study computes the exceedances (or co-exceedances) from the previously calculated distance measurements (DD, DI and DC) of the sample US states and countries. These exceedances will be used as input variables in the MLM model. The outcomes from the exceedances computation demonstrate several interesting patterns. In the case of US states, extreme events tend to occur simultaneously in all the states, although the number of extreme events is significantly higher in DI and DC in comparison to DD. Additionally, for most of the sample countries DI and DD are more stable in condition 1 and 2, which indicates a positive value contagion. On the other hand, the DC values of the sample countries tend to move more into states 3 and 4. As anticipated, the frequency of states 3 and 4 is higher the period 2009–2010 across the entire sample. Additionally, the DD, DI and DC values or India and China never cross into state 4. On the other hand, European countries move into state 3 and 4 more often than their counterparts in the global economy. Generally, the distance to risk values of the financially important US states and the Asian countries demonstrate a tendency to stay within states 1 and 2 throughout the sample period.

5.6. Contagion risk analysis

5.6.1 Distance to default contagion

The results of financial contagion created by DD spillover from US states and from countries in the sample revealed moderate correlation across the samples. In the base model, it calculates contagion by one-day lagged exceedances in the other 14 US states and 19 countries, if their multinomial logistic outcomes are significant (Akhter

& Daly, 2017; Akhter & Hasan, 2015).The model recognises this affect as contagion from those US states or countries into the underlined US state (defined as the dependent variable). Tables 5.6.1.1 to 5.6.1.3 demonstrate the spillover contagion within the US states form the MLM model. In these tables, the model uses the p-value (at 5% c.l.)[16] as the threshold for disturbing, alarming and crisis states (excluding the base state)[17]. Using these Tables, one can see how other countries or US states transfer their value shocks into the target US states within a one-day lag. As previously discussed, the study also adds stock market volatility, world index volatility, GFC and term structure spread as mutual explanatory variables.

[16] The study assesses the contagion influence as most significant at the 5% level for reporting the co-exceedances in the thesis'sMLM model. This is also reinforced by amplified Pseudo R Square in the thesis'sestimation result. Using one-day lagged co-exceedances from other sample US states or countries does not result in any variations in outcomes compared to two- or three-day lagged variables.

[17] The MLM uses the first state as the base outcome and calculates the likelihood of the other states considering the base state. Thus, the outcome of the base state is absent (Matejka & McKay, 2014).

Table 5.6.1.1. DD state 2 Contagion (state to state)

	California	Newyork	Gorgia	Illinois	Indiana	Massachusetts	Michigan	Mississippi	New Jersey	North Carolina	Ohio	Pennsylvania	Taxas	Virginia	West Virginia
Lag number of exceedances: California			0.001						0.003						
Lag number of exceedances: Newyork															
Lag number of exceedances: Gorgia				0.002			0.026						0.004		
Lag number of exceedances: Illinois															0.015
Lag number of exceedances: Indiana						0.017	0.017				0.043			0.006	
Lag number of exceedances: Massachusetts	0.031	0.005										0.002	0.012		
Lag number of exceedances: Michigan															
Lag number of exceedances: Mississippi													0.002		0.048
Lag number of exceedances: New Jersey															
Lag number of exceedances: North Carolina													0.017		
Lag number of exceedances: Ohio															
Lag number of exceedances: Pennsylvania															
Lag number of exceedances: Taxax	0.036														
Lag number of exceedances: Virginia					0.033					0		0.021			
Lag number of exceedances: West Virginia															
Garch Volatility															
World index volatility															
Term Structure															
GFC	0	0	0	0.003	0.001	0.008	0	0.002	0.02	0	0				0

Table 5.6.1.2- DD state 3 Contagion (state to state)

	California	Newyork	Gorgia	Illinois	Indiana	Massachusetts	Michigan	Mississippi	New Jersey	North Carolina	Ohio	Pennsylvania	Taxas	Virginia	West Virginia
Lag number of exceedances: California			0.001												
Lag number of exceedances: Newyork															
Lag number of exceedances: Gorgia							0.011				0				
Lag number of exceedances: Illinois							0.024					0.036			
Lag number of exceedances: Indiana				0.007			0.039								
Lag number of exceedances: Massachusetts	0.001	0.02			0.001			0.036	0.001	0.047	0.002	0.046			0.02
Lag number of exceedances: Michigan															
Lag number of exceedances: Mississippi							0.034			0.027		0.016			
Lag number of exceedances: New Jersey												0.022		0.047	
Lag number of exceedances: North Carolina								0.009							
Lag number of exceedances: Ohio							0.037								
Lag number of exceedances: Pennsylvania		0.01								0.034					
Lag number of exceedances: Taxax		0.003								0.039		0.017			
Lag number of exceedances: Virginia	0.011		0.004										0.048		
Lag number of exceedances: West Virginia															
Garch Volatility															0.003
World index volatility															
Term Structure															
GFC	0	0.004	0	0	0.001	0.014	0	0.019	0	0	0	0.001	0.002	0	0

Table 5.6.1.3- DD state 4 Contagion (state to state)

	California	Newyork	Gorgia	Illinois	Indiana	Massachusetts	Michigan	Mississippi	New Jersey	North Carolina	Ohio	Pennsylvania	Taxas	Virginia	West Virginia
Lag number of exceedances: California					0.018									0.061	0.023
Lag number of exceedances: Newyork				0.047											
Lag number of exceedances: Gorgia				0	0.003				0.042	0.006	0	0.021			
Lag number of exceedances: Illinois					0										
Lag number of exceedances: Indiana															
Lag number of exceedances: Massachusetts				0.003	0.001			0.002				0.003			
Lag number of exceedances: Michigan															
Lag number of exceedances: Mississippi		0.006	0.035		0.009		0.001			0.007	0.027	0.036	0.002	0.006	0
Lag number of exceedances: New Jersey															
Lag number of exceedances: North Carolina															
Lag number of exceedances: Ohio									0.041						
Lag number of exceedances: Pennsylvania															0.037
Lag number of exceedances: Taxax								0.001							
Lag number of exceedances: Virginia			0.037									0.006			
Lag number of exceedances: West Virginia															
Garch Volatility	0.036														
World index volatility															
Term Structure	0.049	0.017										0.033			
GFC	0.002		0	0	0.008	0.003	0	0.002	0.018	0	0	0.001		0.002	0.001

In the next phase, the study collates all the results in Table 5.6.1.4 using the significant p-value from the previous tables, followed by another Table (5.6.1.5) showing correlation among these variables. As expected, Table 5.6.1.5 shows a very high degree of correlation among the US states (around 60%) and a moderate correlation (around 30%) for the rest. Following previous researchers,The thesishave taken this amount of correlation as demonstrating contagion within the sample countries and states (Gerhart, Wright, MAHAN, & Snell, 2000; Shrout & Fleiss, 1979). Table 5.6.5.4 shows us the movement of a particular shock (ranked by 2, 3 and 4) from a particular country or US state to the dependent US state. Looking at the Table, one can observe contagion among the sample states and countries. The most significant finding relate to the scale of shock transmission. The study finds that US states are more influenced by other countries than by other US states, especially when it comes to transmitting extreme financial conditions or crisis states. Another key observation is the ineffectiveness of common explanatory variables (with the exception of the global financial crisis). At this point, the research methodology has divided the discussions into two parts – contagion arising from US states and contagion arising from other countries.

Table 5.6.1.4- DD Contagion

	California	Newyork	Gorgia	Illinois	Indiana	Massachus	Michigan	Mississippi	New Jersey	North Carol	Ohio	Pennsylvan	Taxas	Virginia	West Virgin
Lag number of exceedances: California			23		4				2						
Lag number of exceedances: Newyork				4											
Lag number of exceedances: Gorgia				24	4		23		4	4	34	4	2		
Lag number of exceedances: Illinois					4		3					3			2
Lag number of exceedances: Indiana				3		2	23				2			2	
Lag number of exceedances: Massachusetts	23	23		4	34			34	3	3	3	234	2		3
Lag number of exceedances: Michigan															
Lag number of exceedances: Mississippi		4	4		4		34			34	4	34	24	4	34
Lag number of exceedances: New Jersey												3		3	
Lag number of exceedances: North Carolina								3					2		
Lag number of exceedances: Ohio							3		34						
Lag number of exceedances: Pennsylvania		3							3						4
Lag number of exceedances: Taxax	2	3						4				3			
Lag number of exceedances: Virginia	3		34		2					2		24	3		
Lag number of exceedances: West Virginia															
Lag number of exceedances: KR	4														3
Lag number of exceedances: CH															
Lag number of exceedances: IN	4	4										4			
Lag number of exceedances: BR	234	234	234	234	234	234	234	234	234	234	234	34	3	34	234
Lag number of exceedances: DM	3		234							34	4				
Lag number of exceedances: FR		234	24			2	2			23	3		4		
Lag number of exceedances: GM									2	3	3	2	24		
Lag number of exceedances: IT	4		4	4	4									3	3
Lag number of exceedances: JP	24			3					4		2	4	3	34	
Lag number of exceedances: MY											2	2			
Lag number of exceedances: MX	4	4		4	4	4		4	24		4		34		4
Lag number of exceedances: NL	4		4	24			23	3	4		23	3			
Lag number of exceedances: SA	4			4		4		4	4	4	4	3	4	4	4
Lag number of exceedances: SP											2	4	3		2
Lag number of exceedances: SW				2			2								
Lag number of exceedances: SL			34	4							4				
Lag number of exceedances: UK		24	34	24		24	3			234	234				4
Lag number of exceedances: BE			24		4	2		4	34	234		34	4	23	4
Lag number of exceedances: AU							2			4			4	2	
Garch Volatility	4														3
World index volatility															
Term Structure	4	4										4			
GFC	234	234	234	234	234	234	234	234	234	234	234	34	3	34	234

Table 5.6.1.5- DD Correlation

	ddcal	ddny	ddgor	ddill	ddind	ddmas	ddmic	ddmis	ddnj	ddnc	ddoho	ddpen	ddtex	ddvir	ddwv	ddus	ddau	ddbe	dduk	ddsl	ddsw	ddsp	ddsa	ddru	ddnl	ddmx	ddmy	ddjp	ddit	ddgm	ddfr	dddm	ddbr	ddin	ddch	ddkr
ddcal	1																																			
ddny	0.7054	1																																		
ddgor	0.6647	0.5475	1																																	
ddill	0.7282	0.5976	0.7161	1																																
ddind	0.6642	0.5499	0.6016	0.7033	1																															
ddmas	0.7078	0.6597	0.5895	0.6863	0.6852	1																														
ddmic	0.569	0.5115	0.5943	0.5659	0.4995	0.551	1																													
ddmis	0.6985	0.6172	0.5796	0.6914	0.7173	0.7006	0.5263	1																												
ddnj	0.6903	0.5822	0.6089	0.6974	0.6911	0.6935	0.5356	0.6915	1																											
ddnc	0.6758	0.646	0.6935	0.6678	0.5851	0.6042	0.547	0.5963	0.5962	1																										
ddoho	0.6977	0.6157	0.7128	0.6872	0.5926	0.6368	0.551	0.5856	0.5865	0.6988	1																									
ddpen	0.7506	0.6621	0.6381	0.7323	0.7147	0.7142	0.53	0.7482	0.7024	0.6581	0.682	1																								
ddtex	0.7252	0.6624	0.5596	0.6548	0.654	0.6753	0.4974	0.7385	0.6575	0.6146	0.6138	0.7352	1																							
ddvir	0.5881	0.5099	0.5568	0.6112	0.5569	0.5246	0.4534	0.5632	0.5497	0.5593	0.5422	0.5632	0.5333	1																						
ddwv	0.6712	0.574	0.6272	0.7266	0.708	0.6934	0.5693	0.7258	0.6981	0.6139	0.6063	0.7338	0.6802	0.5662	1																					
ddus	0.6847	0.8932	0.5793	0.6099	0.5279	0.6357	0.5259	0.5814	0.5612	0.6969	0.6321	0.6318	0.6164	0.4996	0.5673	1																				
ddau	0.3386	0.3877	0.2915	0.3081	0.2721	0.3344	0.31	0.2844	0.2853	0.306	0.3575	0.311	0.2965	0.3013	0.2958	0.3783	1																			
ddbe	0.391	0.4219	0.3559	0.3309	0.2907	0.3447	0.2806	0.3386	0.3445	0.4057	0.3437	0.3459	0.3611	0.3034	0.336	0.4205	0.2815	1																		
dduk	0.5325	0.6162	0.4663	0.4704	0.4265	0.5034	0.4535	0.4457	0.4213	0.5354	0.5579	0.5015	0.4748	0.4455	0.4713	0.6072	0.4574	0.4902	1																	
ddsl	0.4756	0.5837	0.3239	0.3692	0.3651	0.4653	0.3504	0.4128	0.3732	0.4231	0.4206	0.4379	0.4433	0.3551	0.4007	0.5536	0.4341	0.4609	0.6066	1																
ddsw	0.4136	0.4421	0.3394	0.3559	0.3217	0.3659	0.3313	0.3245	0.3373	0.3706	0.3969	0.3663	0.3425	0.3042	0.3408	0.4443	0.4017	0.4211	0.5564	0.5326	1															
ddsp	0.3588	0.4052	0.2555	0.2993	0.2893	0.3423	0.2635	0.3067	0.2908	0.3186	0.2896	0.3426	0.3345	0.275	0.2869	0.3702	0.3181	0.4329	0.4758	0.4832	0.4443	1														
ddsa	0.3064	0.3209	0.2287	0.2846	0.2779	0.3081	0.2174	0.3018	0.2823	0.2771	0.3012	0.3161	0.3297	0.2741	0.312	0.3103	0.4884	0.2249	0.358	0.3503	0.3044	0.2547	1													
ddru	0.1398	0.1303	0.074	0.0547	0.0791	0.0988	0.0331	0.0953	0.0964	0.0917	0.0832	0.1104	0.0918	0.074	0.062	0.1476	0.1603	0.1863	0.1654	0.1994	0.2245	0.169	0.2176	1												
ddnl	0.424	0.4589	0.3232	0.3576	0.356	0.3835	0.3377	0.3548	0.3581	0.3689	0.364	0.3661	0.3584	0.3097	0.3318	0.4366	0.3833	0.4672	0.5258	0.5245	0.5032	0.4493	0.3018	0.2229	1											
ddmx	0.3025	0.3652	0.25	0.2776	0.2645	0.3005	0.2565	0.281	0.3097	0.2695	0.2955	0.3102	0.3001	0.2364	0.2716	0.348	0.2756	0.2535	0.3491	0.3643	0.343	0.3032	0.2518	0.1629	0.3149	1										
ddmy	0.2417	0.2724	0.1602	0.1597	0.1564	0.2234	0.1503	0.1996	0.184	0.1907	0.2179	0.2175	0.2338	0.2011	0.1884	0.2426	0.2626	0.2068	0.2659	0.3282	0.2808	0.2125	0.2304	0.1857	0.2614	0.2244	1									
ddjp	0.3262	0.3209	0.2386	0.2655	0.2536	0.2719	0.2403	0.2516	0.2553	0.2741	0.3211	0.3114	0.2935	0.2906	0.2647	0.3176	0.3552	0.2067	0.3607	0.3234	0.3208	0.2376	0.3101	0.1275	0.285	0.2031	0.2719	1								
ddit	0.272	0.354	0.2032	0.2284	0.2138	0.2961	0.2382	0.2524	0.2613	0.2586	0.2388	0.2534	0.2737	0.19	0.2492	0.3381	0.1893	0.4292	0.4091	0.4114	0.3884	0.5093	0.1667	0.1453	0.423	0.2481	0.1768	0.1728	1							
ddgm	0.4	0.4638	0.325	0.3301	0.3702	0.4004	0.3301	0.3771	0.3563	0.3909	0.359	0.3557	0.3491	0.2885	0.3533	0.4519	0.3408	0.482	0.5188	0.5009	0.4876	0.4723	0.2654	0.225	0.5168	0.3362	0.2551	0.2748	0.4758	1						
ddfr	0.3675	0.4605	0.2688	0.3004	0.313	0.3511	0.287	0.3499	0.3205	0.3243	0.3349	0.3523	0.3664	0.2792	0.3158	0.4369	0.3714	0.4272	0.5318	0.5363	0.4866	0.4122	0.3076	0.1957	0.4927	0.2994	0.2737	0.3036	0.3363	0.4561	1					
dddm	0.4495	0.4914	0.4105	0.3669	0.3399	0.4232	0.3901	0.3585	0.3505	0.4468	0.4644	0.4082	0.3859	0.3517	0.3813	0.4872	0.4248	0.4842	0.5802	0.552	0.514	0.4336	0.3127	0.2203	0.5293	0.3126	0.294	0.2972	0.3893	0.5201	0.4665	1				
ddbr	0.1811	0.2404	0.1449	0.145	0.1896	0.199	0.1533	0.1878	0.157	0.1512	0.1971	0.1736	0.1605	0.1682	0.1737	0.219	0.2176	0.0874	0.2556	0.2798	0.2638	0.1225	0.2357	0.1345	0.2381	0.1617	0.2248	0.218	0.1048	0.1906	0.2514	0.2402	1			
ddin	0.1458	0.2305	0.1192	0.1336	0.1343	0.1624	0.1213	0.1463	0.1349	0.1472	0.2004	0.1559	0.1443	0.1337	0.1255	0.2177	0.3094	0.1423	0.2631	0.2829	0.2304	0.17	0.2192	0.1155	0.2132	0.1894	0.2314	0.2263	0.1382	0.2225	0.2168	0.2345	0.1334	1		
ddch	0.204	0.2875	0.142	0.1493	0.165	0.2162	0.1473	0.1899	0.1745	0.1891	0.2181	0.207	0.2291	0.207	0.1764	0.2794	0.2638	0.156	0.2693	0.3097	0.2149	0.2017	0.2058	0.0919	0.2553	0.1855	0.2179	0.2369	0.1625	0.2098	0.2918	0.2078	0.2153	0.2105	1	
ddkr	0.2963	0.3462	0.2341	0.2504	0.2146	0.2565	0.2571	0.2257	0.2802	0.2601	0.2768	0.278	0.2624	0.2135	0.2444	0.3471	0.2776	0.2692	0.3534	0.3756	0.3639	0.2247	0.2293	0.2459	0.3262	0.2786	0.2358	0.3003	0.1959	0.3255	0.3401	0.3503	0.2066	0.1914	0.2284	1

In the first part, the study looks into contagion from "state to state". The most important observation regarding this part is the impact of size. The chart clearly shows larger states can tend to exert a strong influence on their smaller counterparts, as expected; the exception is Massachusetts, which appears to be immune to shocks from all other states excluding Indiana. Pennsylvania, at the other extreme, is the state most often affected by shocks from other states. Among the other large and economically dominant states, California and New York receive shocks from only four states. California, having one of the largest economies of the world, is also immune from level 4 value shocks, in accordance to the findings. Conversely, it transmits shocks to only three states – Georgia, Indiana and New Jersey – which indicates California enjoys a relatively insulated economic position within the USA. New York, the financial capital of the world, only managed to transmit its shocks to Illinois. Massachusetts and Mississippi are the most influential states in terms of transmitting shocks, followed by Georgia and Virginia. Given that Massachusetts experienced transmitted shocks from only one state, while having the highest capacity of transmitting shock to other states, it is one of the most influential states in this context. Notably, West Virginia failed to transmit its value shocks to any other states in the sample.

In the next phase of the analysis, the study look into the contagion from foreign countries to the US states (Table 5.6.1.4). Surprisingly, the amount of spillover from international sources to US states is higher than between the states. This indicates a high level of contagion into the US states from the global economy. Ohio, Pennsylvania, Illinois and Texas are the most affected by the shock transfer from other countries, and New York and Indiana the least affected. In most cases the US states are affected by spillover of level 4 shock, rather than levels 2 or 3; this suggests that most US states can withstand smaller shocks from outside the world but are not immune to extreme value movements proofed by the previous subsections findings. In another unexpected result, The research has found that Brazil was the largest source of spillover to the US states, affecting every state in the sample and followed by Mexico and South Africa. These results demonstrate the ability of the BRICS countries to influence the US economy, previously noted by other researchers (Cheng, Gutierrez, Mahajan, Shachmurove, & Shahrokhi, 2007; Kocaarslan, Soytas, Sari, & Ugurlu, 2018).

5.6.2. Distance to inefficiency contagion

The distance to inefficiency contagion results show a similar pattern to the previous measurements. Using the same technique, the results between US states and countries are shown in Figure 5.6.2.1, followed by the correlation table on figure 5.6.2.2. As expected, as with distance to default the correlation table for DI shows a relatively high level of association between the states, and moderate level between other countries and the US states. Again, other than the GFC none of the common explanatory variables showed any significant impact in the model. Following the previous section, the results are divided into two categories – contagion between US states and contagion between other countries and US states.

Table 5.6.2.1- DI Contagion

	California	Newyork	Gorgia	Illinois	Indiana	Massachus	Michigan	Mississippi	New Jersey	North Carol	Ohio	Pennsylvan	Taxas	Virginia	West Virgin
Lag number of exceedances: California		23	2						4		3		3		
Lag number of exceedances: Newyork														3	
Lag number of exceedances: Gorgia	4			4		2				4	234				
Lag number of exceedances: Illinois						23							2		
Lag number of exceedances: Indiana												2		2	
Lag number of exceedances: Massachusetts	2			3	3			24	4			23	2		
Lag number of exceedances: Michigan		4	34	4	4	34		4	34		4		24		4
Lag number of exceedances: Mississippi														4	
Lag number of exceedances: New Jersey		4													
Lag number of exceedances: North Carolina			4								3	23			
Lag number of exceedances: Ohio			23	3					4						
Lag number of exceedances: Pennsylvania	4	234	3	4	4									4	
Lag number of exceedances: Taxax	3		234								3				
Lag number of exceedances: Virginia	234	24	23	2	23	4		3	34	234	4	234			
Lag number of exceedances: West Virginia		4	2		3	3					2				
Lag number of exceedances: KR	24				3	234	3	2	34	3		2	3	23	234
Lag number of exceedances: CH	2	2		2	23			3	2	2		2			
Lag number of exceedances: IN											3	3			
Lag number of exceedances: BR			2				23			2		3			
Lag number of exceedances: DM		2				2	2				4	2			3
Lag number of exceedances: FR		34					23			2				3	
Lag number of exceedances: GM	34		34	4		4	2		4	3	4		4		
Lag number of exceedances: IT			34	4	234			4			23			234	34
Lag number of exceedances: JP	3	2		4	2				4					3	34
Lag number of exceedances: MY										3		4	3	2	
Lag number of exceedances: MX			3	4								4	4	2	
Lag number of exceedances: NL				3			2				23			3	
Lag number of exceedances: SA	4		4					2	34	4	4	4	34	4	3
Lag number of exceedances: SP									2		3	4	34		3
Lag number of exceedances: SW	3		34	3	24	4		4		3	34				
Lag number of exceedances: SL										3				2	
Lag number of exceedances: UK	34	24		24	34	4	34	4	2		234	234	24	34	4
Lag number of exceedances: BE			24										2		
Lag number of exceedances: AU	234		234	4		3	3		2	2	34				
Garch Volatility		4		4											
World index volatility				4									24		
Term Structure		34		4							2	4	4		
GFC	234	234	234	234	234	234	23	24	234	234	234	234	23	34	234

Table 5.6.2.1- DI Correlation

	dical	diny	digor	diill	diind	dimas	dimic	dimis	dinj	dinc	dioho	dipen	ditex	divir	diwv	dius	diau	dibe	diuk	disl	disw	disp	disa	diru	dinl	dimx	dimy	dijp	diit	digm	difr	didm	dibr	diin	dich	dikr
dical	1																																			
diny	0.6611	1																																		
digor	0.5835	0.5163	1																																	
diill	0.6841	0.5802	0.6974	1																																
diind	0.6188	0.5479	0.5935	0.684	1																															
dimas	0.6796	0.6006	0.5373	0.6541	0.6375	1																														
dimic	0.5065	0.4943	0.5563	0.5592	0.5111	0.5182	1																													
dimis	0.6748	0.582	0.5455	0.6957	0.6797	0.6787	0.5154	1																												
dinj	0.6393	0.5126	0.532	0.6639	0.6462	0.6633	0.5004	0.6871	1																											
dinc	0.6315	0.6252	0.6563	0.6573	0.5614	0.5838	0.5225	0.5666	0.5372	1																										
dioho	0.6354	0.6044	0.7161	0.6701	0.5821	0.5643	0.5634	0.5626	0.5224	0.6566	1																									
dipen	0.7075	0.622	0.5971	0.7307	0.687	0.6874	0.5011	0.7372	0.6835	0.6377	0.654	1																								
ditex	0.6932	0.5945	0.5159	0.6482	0.6196	0.6388	0.4778	0.7075	0.6374	0.5798	0.5721	0.7112	1																							
divir	0.4862	0.4684	0.5225	0.5752	0.5655	0.4834	0.4563	0.5318	0.4782	0.4905	0.5145	0.5315	0.481	1																						
diwv	0.6497	0.5209	0.5515	0.6816	0.7087	0.6358	0.4866	0.6901	0.6581	0.5511	0.5371	0.7018	0.6501	0.5194	1																					
dius	0.6565	0.887	0.5524	0.5944	0.5196	0.5869	0.5035	0.5633	0.5059	0.689	0.6273	0.6122	0.5652	0.454	0.5107	1																				
diau	0.3528	0.3542	0.3389	0.3313	0.2887	0.337	0.348	0.3029	0.288	0.3345	0.4069	0.3267	0.3019	0.2649	0.3085	0.3618	1																			
dibe	0.3128	0.3792	0.3391	0.2982	0.2158	0.2715	0.2669	0.2586	0.2421	0.3692	0.3126	0.2867	0.2718	0.2174	0.2359	0.4052	0.2352	1																		
diuk	0.3523	0.477	0.3714	0.4034	0.4026	0.3768	0.4199	0.3699	0.3034	0.3903	0.4694	0.4021	0.3713	0.3592	0.3535	0.4705	0.3957	0.3035	1																	
disl	0.4355	0.5264	0.3455	0.3666	0.316	0.4335	0.3539	0.3785	0.3146	0.4424	0.3833	0.3764	0.3773	0.307	0.3248	0.5122	0.378	0.4123	0.4419	1																
disw	0.443	0.492	0.4157	0.427	0.3946	0.4263	0.4108	0.4106	0.3518	0.4596	0.4918	0.4058	0.388	0.33	0.3638	0.5064	0.4149	0.4093	0.5072	0.5084	1															
disp	0.3097	0.3527	0.2138	0.2409	0.2013	0.2942	0.201	0.2901	0.2747	0.3215	0.2036	0.2894	0.3003	0.1709	0.2328	0.3459	0.2253	0.4242	0.2244	0.4075	0.3758	1														
disa	0.3019	0.3395	0.2868	0.2882	0.3059	0.2825	0.2682	0.2998	0.2818	0.2971	0.3432	0.3113	0.3098	0.2623	0.2798	0.3239	0.3121	0.1888	0.3684	0.3044	0.339	0.1727	1													
diru	0.0748	0.1061	0.1331	0.0946	0.0649	0.0604	0.0819	0.0821	0.0953	0.1012	0.148	0.0963	0.0966	0.1086	0.0597	0.1317	0.0667	0.1262	0.0569	0.134	0.1579	0.0832	0.1492	1												
dinl	0.372	0.4273	0.3625	0.3388	0.3273	0.3206	0.3345	0.3227	0.3015	0.3965	0.3855	0.3244	0.3134	0.3037	0.2892	0.433	0.3106	0.4537	0.3862	0.4617	0.4803	0.3296	0.3022	0.177	1											
dimx	0.2406	0.2824	0.2393	0.2252	0.209	0.2111	0.1771	0.2101	0.2072	0.249	0.2322	0.2252	0.2379	0.2107	0.1906	0.2819	0.1847	0.2115	0.1831	0.2515	0.2576	0.2004	0.2265	0.1715	0.2396	1										
dimy	0.2343	0.2507	0.2238	0.2347	0.1985	0.2411	0.223	0.2146	0.1903	0.2363	0.2622	0.2382	0.231	0.2246	0.1967	0.2535	0.2575	0.2114	0.2224	0.2591	0.2399	0.1863	0.2067	0.186	0.2735	0.1908	1									
dijp	0.047	-0.0045	-0.0113	0.0098	0.0195	0.0406	-0.0231	0.0058	0.046	-0.0245	-0.0308	-0.0099	-0.0037	-0.0021	0.0565	-0.0026	0.0069	-0.0483	-0.0417	0.0072	-0.0179	0.0082	-0.0202	-0.062	-0.0429	0.0212	0.0049	1								
diit	0.2152	0.281	0.1386	0.1428	0.0923	0.1976	0.1793	0.1907	0.1755	0.2397	0.1305	0.1745	0.1969	0.0679	0.1283	0.2892	0.1552	0.4467	0.1573	0.3529	0.303	0.6184	0.1061	0.0975	0.3598	0.1457	0.1606	0.0001	1							
digm	0.2238	0.3572	0.2055	0.2383	0.2798	0.2557	0.2831	0.2571	0.2251	0.242	0.2678	0.259	0.2342	0.2192	0.2534	0.3315	0.259	0.184	0.4709	0.3239	0.3387	0.1555	0.2561	-0.0119	0.2779	0.1222	0.1614	0.0158	0.1185	1						
difr	0.3001	0.4369	0.3026	0.2999	0.3249	0.3047	0.3755	0.292	0.255	0.3256	0.3925	0.3152	0.3038	0.3145	0.2848	0.4093	0.3433	0.317	0.5061	0.4246	0.3968	0.2458	0.292	0.0856	0.3809	0.154	0.1881	-0.0783	0.2388	0.4275	1					
didm	0.3133	0.3948	0.3503	0.2947	0.2684	0.2952	0.3692	0.2524	0.2447	0.3646	0.3937	0.2865	0.2582	0.2647	0.2493	0.4131	0.3461	0.3502	0.3712	0.3967	0.4195	0.2889	0.2663	0.1297	0.4018	0.2188	0.2402	-0.0484	0.2709	0.2446	0.363	1				
dibr	0.0928	0.1476	0.0796	0.0723	0.0966	0.1184	0.0855	0.1346	0.0715	0.0967	0.1075	0.1021	0.1064	0.1201	0.0733	0.1507	0.1086	0.0987	0.1084	0.1393	0.1377	0.1125	0.1435	0.167	0.1279	0.1617	0.1357	-0.0417	0.0808	0.0771	0.0658	0.1176	1			
diin	0.1257	0.1876	0.1248	0.1263	0.1299	0.1635	0.1652	0.1422	0.1126	0.1477	0.1754	0.111	0.1295	0.1155	0.1132	0.1921	0.2048	0.106	0.2107	0.1706	0.1984	0.1194	0.1498	0.0256	0.16	0.0888	0.1272	0.0096	0.0961	0.2561	0.1978	0.1726	0.0684	1		
dich	0.0536	0.0816	0.0718	0.0321	0.0252	0.081	0.0564	0.0667	0.0566	0.0619	0.0943	0.0627	0.0614	0.0763	0.0353	0.094	0.0654	0.1085	0.0607	0.1487	0.102	0.1149	0.1019	0.158	0.0868	0.1485	0.1087	-0.0042	0.1113	0.0113	0.0536	0.0599	0.067	0.0575	1	
dikr	0.0966	0.0235	-0.0145	0.0393	0.0499	0.0962	-0.0094	0.0578	0.0804	0.0034	-0.0159	0.0322	0.0525	-0.0546	0.0863	0.0175	0.0439	-0.031	-0.0353	0.0581	0.0266	0.0647	0.0075	-0.1148	-0.001	0.05	0.0189	0.2941	0.015	0.0266	-0.0578	-0.0174	-0.0262	0.0105	0.002	1

The results show similar financial contagion patterns between states as the previous section on DD, but with a more even distribution of shocks. The size of a state's economy does not appear to play a role in this measure of systemic risk. As per the MLM's findings, Georgia, New York and Ohio are most affected by contagion from other states, followed by California, Massachusetts and Indiana. Michigan is totally immune from shock transfer from any other states. Additionally, economically less important states (based on states current economic output in US economy) such as North Carolina and West Virginia are also highly immune from shock transfer. From a different perspective, Virginia and Michigan played the most prominent role in transferring shocks to other states, followed by Massachusetts. In a somewhat surprising outcome, shocks in highly economically developed states like California and New York spilled over to very few states, placing them on a par with less significant states like Mississippi, North Carolina and Illinois.

Turning to the spillover from the sample countries, Table 5.6.2.1 shows an increased movement of categorised shocks, as see before (with DD). Most countries transmitted their DI value shocks to the US states. The one apparent anomaly in this context is New York, which is able to withstand spillover from most countries. The chart also shows that European counties (excluding Belgium) are more capable of transferring their shocks to the US states, while the developing economies and BRICS countries, like India, Brazil and Malaysia, have less influence on the inefficiency measures of US states.

5.6.3. Distance to capital contagion

Overall the distance to capital contagion measure presents similar results, following the pattern of the two previous distance measures. The estimation results and the correlation table are provided in Table 5.6.3.1 and Table 5.6.3.2 respectively. As with the previous two sets of results, the level of correlation increases in distance to capital contagion. The overall result displays a strong association among the variables; again, the GFC is the only influential common explanatory variable. To discuss the results, the results are again divided into two parts, contagion between the US states and contagion from foreign countries to US states.

Consistent with the previous results, there is a high level of systemic risk contagion between the US states. Indiana, Ohio and Virginia are most affected by the systemic risk spillover from other states, followed by Illinois and North Carolina. On the other hand, only one state generated spillover to Massachusetts and Pennsylvania. Supersized economies like California and New York showed a very high level of shock resistance in relation to other states. Pennsylvania and New Jersey transmitted the greatest number of shocks to other states, while New York was the lowest, with only one shock transmission (to Indiana). Looking at country-level contagion to US states, the UK, Belgium, India and Mexico influenced the largest number of US states, while Korea, Brazil, Italy and Sweden fail to have any significant impact. At the other end of the spillover, smaller states experienced more shocks than their larger counterparts did. The results also show that all states are affected by spillover (using DC) from the sample countries with the sole exception of New York, which again resisted most extreme value shocks calculated by distance to capital.

Table 5.6.3.1- DC Contagion

	California	Newyork	Gorgia	Illinois	Indiana	Massachus	Michigan	Mississippi	New Jersey	North Carol	Ohio	Pennsylvan	Taxas	Virginia	West Virgin
Lag number of exceedances: California			2	4	4				2		3			23	
Lag number of exceedances: Newyork					4										
Lag number of exceedances: Gorgia	4									4	34		4		
Lag number of exceedances: Illinois			3				3				3				2
Lag number of exceedances: Indiana							3	2		3				4	
Lag number of exceedances: Massachusetts	3			4	34				24		3	4			
Lag number of exceedances: Michigan														3	2
Lag number of exceedances: Mississippi				2	4				2	3	2			3	4
Lag number of exceedances: New Jersey			34	2	24	4				3	3		3		4
Lag number of exceedances: North Carolina				2									2		
Lag number of exceedances: Ohio		2	3							3				3	
Lag number of exceedances: Pennsylvania	24	3	4	4	24		4	4			4		4	4	
Lag number of exceedances: Taxax	24									2					
Lag number of exceedances: Virginia							23		3						
Lag number of exceedances: West Virginia			2		23										
Lag number of exceedances: KR			3							3			2		
Lag number of exceedances: CH						2	2							2	234
Lag number of exceedances: IN	234	4	4	4	34	234	234	4		4	234	24	24	234	
Lag number of exceedances: BR								2		4	23				2
Lag number of exceedances: DM										4	4		4	2	
Lag number of exceedances: FR				2			3	24	4				4		4
Lag number of exceedances: GM			4	34	4	2	34		23					3	
Lag number of exceedances: IT				2											
Lag number of exceedances: JP	4			3	4		4			4	4			234	
Lag number of exceedances: MY			2										3	4	2
Lag number of exceedances: MX	4	4	3	4		34		4	234	4	4	4	4	2	4
Lag number of exceedances: NL			4					2			3				4
Lag number of exceedances: SA			24	4					3	4	3		4	4	4
Lag number of exceedances: SP												3			
Lag number of exceedances: SW	3	2													
Lag number of exceedances: SL			34	24	24	2	4	2	2			4		4	
Lag number of exceedances: UK	4	34	4	24	34	24	34	4	2	34	4	4	234	234	
Lag number of exceedances: BE	3	2	24	3	24	23	2	4	2	4				234	34
Lag number of exceedances: AU								4					34	3	34
Garch Volatility	24			2						234			4	34	3
World index volatility	2		3		2					2				3	
Term Structure		3													2
GFC	24	23	234	234	23	234	234	4		34	234	3		234	4

Table 5.6.3.2- DC Correlation

	dccal	dcny	dcgor	dcill	dcind	dcmas	dcmic	dcmis	dcnj	dcnc	dcoho	dcpen	dctex	dcvir	dcwv	dcus	dcau	dcbe	dcuk	dcsl	dcsw	dcsp	dcsa	dcru	dcnl	dcmx	dcmy	dcjp	dcit	dcgm	dcfr	dcdm	dcbr	dcin	dcch	dckr
dccal	1																																			
dcny	0.6836	1																																		
dcgor	0.6895	0.5802	1																																	
dcill	0.7034	0.574	0.7029	1																																
dcind	0.6693	0.5246	0.6533	0.7031	1																															
dcmas	0.7089	0.6145	0.6604	0.6884	0.6788	1																														
dcmic	0.5937	0.4914	0.6261	0.6315	0.596	0.6167	1																													
dcmis	0.7149	0.5819	0.6742	0.7097	0.7307	0.6968	0.6055	1																												
dcnj	0.5809	0.4954	0.5812	0.5911	0.61	0.5952	0.5323	0.5911	1																											
dcnc	0.7025	0.666	0.7006	0.673	0.6262	0.6482	0.5664	0.6386	0.5363	1																										
dcoho	0.7105	0.629	0.7091	0.6537	0.6108	0.6626	0.5574	0.6277	0.5119	0.7285	1																									
dcpen	0.7466	0.6076	0.69	0.7018	0.7054	0.683	0.5865	0.7299	0.6152	0.6582	0.6884	1																								
dctex	0.7334	0.6201	0.6617	0.6774	0.6666	0.6762	0.5541	0.7416	0.567	0.6738	0.68	0.713	1																							
dcvir	0.6134	0.5382	0.6462	0.6531	0.6081	0.6073	0.6043	0.6101	0.5137	0.6367	0.6177	0.5979	0.5448	1																						
dcwv	0.6502	0.5188	0.6356	0.6697	0.7047	0.6555	0.5969	0.6922	0.6141	0.6068	0.5823	0.7282	0.6615	0.5728	1																					
dcus	0.6603	0.8994	0.6046	0.5917	0.5204	0.6094	0.514	0.5684	0.4965	0.6928	0.6358	0.5922	0.5892	0.5498	0.5057	1																				
dcau	0.2837	0.3396	0.2688	0.2524	0.2295	0.2834	0.2701	0.2258	0.2075	0.2974	0.2989	0.2481	0.225	0.2772	0.2096	0.3361	1																			
dcbe	0.3037	0.351	0.2794	0.2647	0.2707	0.3126	0.2349	0.2884	0.2247	0.2968	0.2613	0.2576	0.255	0.2988	0.2628	0.3361	0.1849	1																		
dcuk	0.4469	0.5239	0.4182	0.4093	0.4126	0.4491	0.4102	0.4092	0.3217	0.4732	0.4598	0.4232	0.4251	0.4553	0.3979	0.5052	0.4191	0.3323	1																	
dcsl	0.4118	0.5114	0.3316	0.3062	0.3237	0.4061	0.3087	0.3598	0.2781	0.4025	0.3909	0.3577	0.3799	0.3393	0.339	0.4863	0.3943	0.4417	0.5307	1																
dcsw	0.4043	0.4696	0.3125	0.3185	0.3162	0.3792	0.2847	0.322	0.274	0.3816	0.3547	0.3417	0.3561	0.2959	0.3138	0.4438	0.3676	0.3443	0.4468	0.5172	1															
dcsp	0.3677	0.4156	0.3046	0.3053	0.318	0.3601	0.2784	0.2994	0.2636	0.3141	0.3073	0.3287	0.3282	0.2966	0.2882	0.3791	0.3055	0.344	0.4626	0.4815	0.5395	1														
dcsa	0.3131	0.3048	0.2545	0.283	0.2852	0.3066	0.245	0.2771	0.2339	0.2949	0.2929	0.2872	0.3197	0.2798	0.288	0.3013	0.3178	0.2489	0.3661	0.343	0.3114	0.324	1													
dcru	0.1397	0.1646	0.0625	0.0768	0.1056	0.1116	0.027	0.1053	0.0809	0.13	0.0962	0.1068	0.1023	0.0677	0.0851	0.1607	0.1222	0.1789	0.1458	0.1895	0.2523	0.1925	0.2434	1												
dcnl	0.3234	0.4071	0.2396	0.2661	0.3212	0.3449	0.2336	0.305	0.2403	0.3096	0.2796	0.311	0.291	0.2559	0.2742	0.3686	0.3151	0.4199	0.4118	0.4855	0.4735	0.4542	0.3369	0.269	1											
dcmx	0.282	0.3447	0.2539	0.2741	0.2854	0.2959	0.2482	0.2852	0.2854	0.2688	0.28	0.2716	0.2965	0.2345	0.2398	0.336	0.2367	0.2039	0.2863	0.3346	0.3033	0.3138	0.2492	0.1696	0.2828	1										
dcmy	0.2174	0.2842	0.1665	0.1415	0.1419	0.2036	0.1559	0.1794	0.1536	0.2109	0.2073	0.1729	0.2217	0.1557	0.1468	0.2429	0.2248	0.1959	0.254	0.3097	0.2716	0.2288	0.2195	0.1551	0.2464	0.1969	1									
dcjp	0.3389	0.3704	0.2943	0.2738	0.2962	0.3035	0.2887	0.2788	0.2	0.3493	0.3497	0.2818	0.3097	0.3354	0.25	0.3647	0.324	0.1808	0.3903	0.3275	0.3392	0.309	0.3122	0.1218	0.2289	0.2049	0.2562	1								
dcit	0.304	0.3555	0.2735	0.2363	0.2366	0.3079	0.2272	0.2326	0.2429	0.2816	0.2788	0.2841	0.2739	0.2311	0.2312	0.3302	0.1987	0.3122	0.3885	0.3622	0.4025	0.4622	0.2205	0.1605	0.3398	0.2449	0.1793	0.2099	1							
dcgm	0.3296	0.3705	0.2957	0.2987	0.3243	0.3381	0.3206	0.3144	0.2962	0.2872	0.2985	0.298	0.28	0.2828	0.2928	0.3763	0.2794	0.2873	0.394	0.3838	0.4202	0.4296	0.2493	0.1991	0.4353	0.2842	0.2125	0.2498	0.3482	1						
dcfr	0.408	0.4786	0.3282	0.3234	0.3553	0.3754	0.3062	0.352	0.3018	0.3832	0.3457	0.3681	0.3769	0.3211	0.3246	0.4486	0.3477	0.4301	0.5389	0.525	0.5164	0.4942	0.307	0.192	0.5058	0.2884	0.253	0.3021	0.4514	0.4254	1					
dcdm	0.4208	0.4884	0.3713	0.3362	0.335	0.3979	0.3327	0.3258	0.3035	0.4201	0.415	0.3721	0.3673	0.3593	0.331	0.4597	0.3843	0.3414	0.5088	0.5124	0.526	0.4821	0.3318	0.2373	0.44	0.2926	0.2756	0.3387	0.3643	0.4189	0.4843	1				
dcbr	0.1915	0.2547	0.1893	0.1612	0.1936	0.2178	0.1853	0.1865	0.1456	0.2018	0.2102	0.1776	0.1773	0.233	0.1731	0.248	0.2055	0.1663	0.3913	0.2982	0.2172	0.2014	0.2142	0.1687	0.2511	0.1764	0.2034	0.2063	0.2081	0.207	0.269	0.2738	1			
dcin	0.0913	0.1702	0.0959	0.0783	0.0988	0.1009	0.0663	0.0835	0.1112	0.1365	0.1157	0.0836	0.0695	0.1013	0.0661	0.1587	0.2056	0.1738	0.2662	0.2105	0.1416	0.204	0.177	0.149	0.1942	0.1254	0.1568	0.1554	0.1854	0.1523	0.1829	0.1936	0.1822	1		
dcch	0.2358	0.3192	0.1944	0.1848	0.2013	0.2508	0.2188	0.2008	0.1871	0.2543	0.2498	0.2113	0.2371	0.2407	0.2053	0.3111	0.2591	0.1996	0.4083	0.296	0.2193	0.2256	0.2101	0.1057	0.2884	0.1883	0.2073	0.2388	0.2669	0.2351	0.3247	0.2692	0.3089	0.2304	1	
dckr	0.3123	0.3714	0.2725	0.2643	0.2428	0.2945	0.2636	0.247	0.234	0.2921	0.2742	0.2724	0.2649	0.2627	0.2372	0.3833	0.2421	0.2563	0.3365	0.389	0.3771	0.2953	0.2346	0.2379	0.3078	0.2622	0.1988	0.3001	0.2684	0.3257	0.3378	0.363	0.2012	0.1385	0.2447	1

5.6.4. Overall contagion

Overall, the contagion risk analyses (based on DD, DI and DC) show a scattered but moderate level of contagion between the US states, and scattered but extreme contagion from foreign countries to US states. Smaller states are transmitting and receiving more value shocks than their larger counterparts, while the larger states show greater resistance to shock than their smaller counterparts. Two of the largest US states (in economic terms), California and New York, transmit the fewest shocks to the other states. But perhaps the most important observation of this chapter concerns the transmission of categorical shocks. Larger shocks are more contagious that the smaller shocks, given their impact. The contagion is also consistent between the states and countries, which indicates a high level of validation of the results.

5.7. Conclusion

This chapter explored the contagion risk for the US banking sector divided by states using three diverse distance to risk procedures. Extreme shocks for US states were modelled as a function of extreme shocks faced by other US states or countries. Four distinct settings of financial stress were formulated for this purpose. The likelihood of these stress conditions moving through the sample were calculated using a multinomial logistic model.

Generally, the results from all three diverse distance to risk procedures indicated robust correlation between the US states' banking systems and other states and countries. The results also indicate that larger states are immune from financial shock to a higher degree. The findings suggest that the critical task is to protect acceptable levels of correlation through cross-state regulation among banks at the international level to secure a safe, stable and sound financial future. Financial institutions should also look into the deeper impact of credit regulation through Basel implementation and its impact on cross- border systemic risk spillover, given that these findings show contagion varies significantly between DC and DD (given DC is “DD calculated with Basel requirement”).

Chapter 6. Interbank contagion in US

6.1. Introduction

This chapter discusses the contagion risk for the US banking sector (as represented by sixty of the large US banks) using the three different distance to risk methods (distance to default, distance to inefficiency and distance to capital) described earlier. This chapter differs from the previous chapter in using a different source to identify contagion. In this chapter, rather than looking into geographical contagion inside the US, this chapter looks into bank-to-bank contagion to better understand spillover specifically among the banks. To address this research goal, the chapter observes the movement of systemic risk in the top 4 banks in each of the 15 US state in the thesis's sample. The study then look into how these shocks transfer from one bank to another in the sample. The final results show an evenly distributed contagion between the US banks. They also indicate that minor banks are both diffusing and receiving more value shocks than their larger counterparts, while larger banks showing higher resistance to shock than their smaller colleagues in all three of the distance to risk measures. In this regard, the study has found no evidence of the superiority of GSIB banks; two of the largest US banks, Citi and JP Morgan, are among the least active. This primarily because of the nature of their business, which is more global then local (Demirer, Diebold, Liu, & Yilmaz, 2018; Glasserman & Loudis, 2015) thus these two banks reluctance to receive or spreading value shocks in the results. Perhaps the most important aspect of this study is the findings that point to the minimal amount of "extreme financial state" bias in contagion risk across all three distance to risk measures. The study also founds that DD has the strongest spillover effect (compared to DI and DC). Additionally, contagion is steady across the banks for the different distance to risk measures, which validates the outcomes of the previous chapters.

6.2. Extreme event calculation

As the study has already calculated distance to default, distance to inefficiency and distance to capital for the individual sample banks in the previous chapter, this chapter starts by calculating the extreme events (exceedances) from these distance measurement (DD, DI and DC) values of US banks. These will be used as input variables in the logistic regression model. The results from the exceedances calculation reveal several interesting patterns. In case of most banks, extreme events tend to materialise simultaneously in all the states, although there are fewer extreme events in relation to DI and DC than there are for DD. Additionally, DC values tend to move more into extreme events. As expected, exceedances that are more frequent are detected during the GFC period.

6.3. Contagion risk analysis

6.3.1. Distance to default contagion

The overall result of the contagion risk analysis using DD shows a highly correlated banking industry within the USA. The multinomial logistic regression results and correlation analysis are provided in Table 6.3.1.1 and Table 6.3.1.2. The results from the correlation analysis table clearly indicate high correlation across US banks (an average of 45%). The amount of correlation increases where there is a positive outcome from the logistic regression table (6.3.1.1) for those banks. In order to present the results in a more simplified manner, the chapter has used p-value (with

5% confidence interval)[18] for analysis (exclusive of the base state)[19]. The results in Table 6.3.1.1 use banks moving their value shocks to the host bank within a one-day lag period as the criterion of financial contagion.

On average, most of the banks receive broadly similar numbers of shocks from other banks. However, some banks show different trends, being affected more severely by their peers (e.g. Ameris Bancorp, MB Financial Inc, First Merchants Corporations and Towne Bank), while others are less affected (e.g. SVB Financial Group, Hancock Holding Company, Renasant Corporations and Isbanco Inc). Banks from Mississippi (for example Hancock Holding Company and Renasant Corporations) tend to be more affected by the movement of extreme shocks than other states. In terms of transmitting shocks, three banks display significantly higher impact – Synovus Financial Corp, First Merchants Corp and Suntrust Bank. Conversely, three banks – FNB Corporations, Isbanco and Comerica Incorporated – show significantly lower influence in generating spillover.

Of the largest banks globally (i.e. 4th bracket GSIB banks), Citi was affected by shocks from JP Morgan, Synovus, First Merchants, Berkshire, PNC Financial Services and Premier Financial Bancorp. It transmitted its own shocks to Goldman,

[18] The study assess that the contagion influence is most significant at 5% level for reporting the co-exceedances in the thesis's MLM model. Amplified Pseudo R Square in the thesis's estimation result also reinforces this. Using one-day lagged co-exceedances produces no significant variations in results compare to two- or three-day lagged variables.

[19] The MLM uses the first state as the base outcome and calculates the probability of other states occurring considering the base state. Thus the outcome of the base state is absent (Matejka & McKay, 2014).

Ameris, United Commercial, First Bushey, Independent and Bank of America. JP Morgan experienced spillover from Suntrust, Wintrust, First Merchants, Prosperity and Premier while transmitting its own shocks to Citi, Goldman, MB Financial, Connectone, Leakland, Provident, Vally National and Premier. An interesting observation is that JP Morgan transmitted shocks to all the sample banks in New Jersey suggesting a close relationship between the two.

Overall, these results provide evidence of moderate home state bias in both receiving and transmitting shocks for most banks. The GSIB banks did not display a significantly higher level of influence in transmitting or receiving shocks; this may indicate that big banks in the US are more dependent on international business than their local counterparts (Haas & Lelyveld, 2014).

Table 6.3.1.1- DD Contagion

	cathey	svb	wells	charles	mellon	citi	goldman	jpmorgan	ameris	suntrust	synovus	unitedcon	firstbusey	firstmidw	mb	wintrust	1stsource	firstmerch	oldnation	leaklandir	berkshire	bostonpri	brookline	statestree	chemical	enterprise	flagstar	independ	trustmark	bancorpsc
cathey									0.02	0.045										0.035										
svb									0.023				0.016																	
wells									0.018									0.031						0.007						0.004
charles															0.009		0.032				0.031									
mellon																														
citi							0.015		0.004			0.027	0.001															0.006		
goldman																						0.022								
jpmorgan						0.017	0.004								0.039															
ameris																		0.003							0.042					
suntrust					0.013			0.033					0.024	0.028		0			0.036			0.013	0.013			0.032			0.012	0.01
synovus	0.048		0.026			0.025				0.014		0.001						0.011						0.012						
unitedcommunity														0.011		0.009					0.011									
firstbusey	0.033										0.002	0.037																		
firstmidwest			0												0.01															
mb																		0.018									0	0.014		
wintrust					0.036				0.044						0.035					0.049										0.002
1stsource								0.045																				0.025		
firstmerchants	0.001			0.041	0.031	0.007	0.003	0.016	0.001				0.028		0.01	0.003	0.001		0.026	0.038		0.02	0.011	0.006	0.001	0.017			0	
oldnational																0							0.014					0.028		0.003
leaklandindiana													0.005																	
berkshire													0.012					0							0.041					
bostonprivate		0.01			0.001		0.038								0.001				0.013							0.023			0.018	
brookline										0.016									0.044											
statestreet		0.013			0									0.004					0.038											0.026
chemical									0.015								0.016			0.005									0.016	
enterprise																														
flagstar														0.003		0.035						0.001			0.005			0.028		
independent	0.004										0.002						0.009	0.045									0.018			
trustmark	0.003																													
bancorpsouth																												0.003		
hancock				0.032											0.043		0.03		0.025									0.017		
renasant		0.03												0.007				0.024		0.005										
connectone																														
leakland																										0.048				
provident													0.023																	
valley																0.024														
bankofamerica	0.008											0.043	0.039			0.006		0.018				0.006	0.019							
bbnt																														0.014
firstcitizen												0.047						0												
yadkin												0.042														0.029				
fifththird																													0.006	
firstdefiance									0.046							0.039				0.033										
huntington					0.048																						0.04			
keycorp			0.049							0.02	0.021																			
northwest																											0.003			
fulton				0.027					0.033			0.015																		
fnb																														
pnc						0.021	0																				0.026			
comerica																														
prosperity								0.005										0.017						0.01						
texas							0						0.004														0.047			
cullenfrost										0.042					0.03															
capitalone				0.014			0.001																	0.024						0.042
freddiemac									0.021		0.032																			
towne																					0.002									
union									0.005																	0.009				
premier				0.017		0.017	0.013	0.014	0.048	0.02								0.035												
city	0.032														0.033			0.047			0.023		0.02	0.049						
wesbanco																														
united			0.01												0.037			0.012										0.047		

	hancock	renasant	connector	leakland	provident	valley	bankofam	bbnt	firstcitizer	yadkin	fifththird	firstdefiar	huntingto	keycorp	northwest	fulton	fnb	pnc	comerica	prosperity	texas	cullenfros	capitalone	freddiema	towne	union	premier	city	wesbanco	united
cathey			0.006																						0.031	0.016				
svb															0.039										0.007					
wells													0.029												0.029					
charles																											0.035			
mellon							0.004														0.042	0.027								
citi							0.001																							
goldman																						0.028			0.036					
jpmorgan			0.048	0.021	0.028	0.041																					0.011			
ameris																		0.019					0.048		0.028					
suntrust	0.027	0.001		0.017	0.005	0.001		0.02		0.04	0.027				0.011				0.001	0.04	0.006	0			0.049			0.048		0.019
synovus									0.021		0.043		0	0							0.007									0.032
unitedcommunity				0.01		0.013					0.004		0.024												0.009					
firstbusey																										0.041				
firstmidwest	0.045									0.01								0.003												
mb							0.02				0.008																			
wintrust										0.008							0.012	0.044				0.048					0.049			
1stsource																									0.032			0.038		
firstmerchants	0.003			0.001		0.01	0.002								0.003	0	0.022	0.042	0.011	0.009	0.045		0					0.001		0.003
oldnational									0.038							0.001			0.026					0.042						
leaklandindiana								0.047				0.034																		
berkshire																														
bostonprivate													0.013	0.024																
brookline						0.049														0.002								0.001		
statestreet						0.006	0.005		0.016					0.002		0.021			0.005									0.009		
chemical		0.013		0.013											0.014										0	0.043				
enterprise																														
flagstar	0.007																													
independent																				0.017										
trustmark															0.01						0.023					0.016				
bancorpsouth											0.044									0.002										
hancock						0.012										0.015			0.003	0.001	0.02	0.037			0.008					0.044
renasant	0.001												0.027				0.013				0.04								0.034	
connectone																														
leakland																									0.015					
provident			0.037														0.015													
valley		0.005																									0.018			
bankofamerica					0.048															0.016										
bbnt																						0.001								
firstcitizen												0.021																		
yadkin				0		0.02															0.014									
fifththird																														0.016
firstdefiance																												0.007		
huntington																							0.005				0.01	0.048		
keycorp								0.006	0.026		0.017																			
northwest																														
fulton									0.001																			0.001	0.008	
fnb							0.018					0.003																		
pnc																								0.005						
comerica															0.005			0.02												
prosperity	0.007												0.026			0.027			0.025		0.022									
texas								0.015																						
cullenfrost										0.035																		0.008		
capitalone																							0							
freddiemac									0.042																	0.038				
towne															0.043															
union				0.039																					0.028					
premier				0.023	0.039	0.016						0.03			0.014	0.015														
city						0.023			0.03									0.002												
wesbanco									0.001												0.012									
united						0.036	0.02	0.005			0.015		0.044															0.008		

Table 6.3.1.2- DD Correlation

	cathey	svb	wells	charles	mellon	citi	goldman	jpmorgan	ameris	suntrust	synovus	edcommu	firstbusey	rstmidwes	mb	wintrust	1stsource	stmerchan	ldnationa	klandindia	berkshire	ostonpriva	brookline	tatestreet	chemical	nterprise	flagstar	depender	trustmark	ancorpsout
cathey	1																													
svb	0.4478	1																												
wells	0.5557	0.4741	1																											
charles	0.3486	0.4386	0.3791	1																										
mellon	0.4124	0.4214	0.4863	0.4324	1																									
citi	0.4247	0.3617	0.501	0.3469	0.392	1																								
goldman	0.3597	0.3705	0.4674	0.4396	0.4383	0.5104	1																							
jpmorgan	0.4503	0.4432	0.6027	0.4283	0.4528	0.5667	0.57	1																						
ameris	0.4763	0.309	0.4438	0.2487	0.2984	0.3706	0.2805	0.3931	1																					
suntrust	0.564	0.5069	0.6147	0.3445	0.4346	0.4769	0.4112	0.5308	0.4452	1																				
synovus	0.5459	0.3861	0.5024	0.2471	0.3389	0.4164	0.309	0.4281	0.4143	0.587	1																			
nitedcommunit	0.4268	0.3158	0.366	0.2325	0.2566	0.3087	0.197	0.3106	0.3132	0.4014	0.4202	1																		
firstbusey	0.4887	0.3489	0.4186	0.2367	0.2918	0.3305	0.2286	0.3488	0.4098	0.4156	0.4249	0.3886	1																	
firstmidwest	0.6346	0.4471	0.5321	0.3379	0.4249	0.4406	0.3665	0.4502	0.4628	0.5885	0.541	0.4404	0.4942	1																
mb	0.5676	0.4603	0.5144	0.3273	0.4199	0.4077	0.3466	0.4502	0.4586	0.5216	0.4262	0.3699	0.4782	0.6222	1															
wintrust	0.5575	0.4338	0.5172	0.3206	0.3902	0.4149	0.3461	0.475	0.3895	0.5342	0.4803	0.3881	0.4287	0.6114	0.4997	1														
1stsource	0.4681	0.3525	0.4444	0.2658	0.3446	0.337	0.3166	0.3979	0.468	0.4265	0.3859	0.3475	0.4115	0.501	0.4898	0.5059	1													
firstmerchants	0.4402	0.3592	0.392	0.2602	0.3236	0.3109	0.2733	0.3635	0.4397	0.4183	0.4045	0.3327	0.3826	0.5081	0.4684	0.4454	0.4195	1												
oldnational	0.5226	0.4514	0.5278	0.3626	0.3899	0.3706	0.3709	0.4813	0.4642	0.4788	0.4619	0.3735	0.4166	0.6098	0.5265	0.5576	0.4485	0.4686	1											
leaklandindiana	0.3702	0.2958	0.3755	0.3223	0.3252	0.3173	0.3163	0.3371	0.3562	0.3346	0.2833	0.2808	0.3485	0.4276	0.376	0.3419	0.4692	0.3778	0.3788	1										
berkshire	0.3389	0.2811	0.3284	0.2346	0.2603	0.2589	0.2686	0.2981	0.2951	0.3166	0.3247	0.2237	0.3126	0.3519	0.338	0.3567	0.3752	0.3393	0.3751	0.2477	1									
bostonprivate	0.5549	0.3999	0.4663	0.2963	0.3809	0.3947	0.3091	0.4066	0.4101	0.4953	0.5013	0.4057	0.4114	0.5602	0.5112	0.4931	0.4442	0.443	0.4974	0.3713	0.3046	1								
brookline	0.3936	0.3522	0.4031	0.3066	0.3311	0.3623	0.3745	0.3666	0.323	0.3578	0.3053	0.246	0.3117	0.4369	0.4231	0.4444	0.4153	0.3625	0.4686	0.3417	0.3787	0.3653	1							
statestreet	0.3967	0.4373	0.4824	0.4533	0.556	0.4092	0.4245	0.4565	0.363	0.4322	0.337	0.2682	0.3339	0.4413	0.4176	0.3812	0.3421	0.3264	0.3996	0.3119	0.2225	0.346	0.376	1						
chemical	0.4247	0.4393	0.4737	0.3247	0.3378	0.3821	0.3864	0.4553	0.4237	0.4332	0.3781	0.313	0.3917	0.4985	0.4869	0.498	0.5438	0.4617	0.5003	0.4716	0.4237	0.3928	0.4507	0.3587	1					
enterprise	0.4444	0.3694	0.3745	0.2818	0.37	0.3115	0.2961	0.3601	0.4223	0.3866	0.3688	0.3213	0.3565	0.4462	0.4435	0.3757	0.4207	0.3804	0.4041	0.3579	0.3108	0.3993	0.3106	0.355	0.4195	1				
flagstar	0.3405	0.1921	0.2384	0.1904	0.2042	0.3092	0.2455	0.2878	0.245	0.273	0.3288	0.2589	0.2108	0.2978	0.2722	0.2991	0.2835	0.2496	0.2725	0.2153	0.2552	0.3361	0.2413	0.1803	0.2914	0.2604	1			
independent	0.3861	0.2294	0.2928	0.1815	0.1748	0.288	0.2277	0.2595	0.284	0.3118	0.3766	0.3268	0.2652	0.3536	0.3024	0.2681	0.2311	0.2559	0.2824	0.1727	0.2068	0.3617	0.1975	0.2121	0.2502	0.2948	0.2883	1		
trustmark	0.5032	0.4356	0.5256	0.38	0.4194	0.3991	0.3836	0.4824	0.419	0.4879	0.4469	0.3649	0.3637	0.5718	0.5063	0.5128	0.5428	0.4137	0.5765	0.4385	0.3707	0.5129	0.4687	0.4239	0.5053	0.3826	0.2908	0.2758	1	
bancorpsouth	0.4405	0.4228	0.4776	0.3542	0.4055	0.3848	0.3916	0.4752	0.3722	0.4683	0.3993	0.3035	0.3028	0.5057	0.4557	0.4564	0.4241	0.378	0.483	0.3929	0.2781	0.404	0.4119	0.3692	0.4633	0.3808	0.2667	0.2103	0.5433	1
hancock	0.4579	0.415	0.4165	0.3591	0.3434	0.3309	0.3157	0.4382	0.3213	0.3838	0.3608	0.313	0.3367	0.4641	0.4574	0.4414	0.402	0.3682	0.5007	0.3387	0.3295	0.399	0.3695	0.3332	0.4265	0.3639	0.2288	0.2502	0.5133	0.4762
renasant	0.4595	0.3898	0.4344	0.2935	0.3302	0.3827	0.3325	0.4231	0.4287	0.4428	0.377	0.3216	0.3757	0.4778	0.4666	0.4138	0.4373	0.3896	0.4756	0.3512	0.3417	0.4159	0.4009	0.3645	0.5125	0.3977	0.2538	0.2682	0.4412	0.393
connectone	0.2055	0.1972	0.1958	0.2399	0.182	0.1882	0.21	0.206	0.1857	0.2017	0.204	0.2052	0.2054	0.2492	0.2116	0.2067	0.2103	0.2329	0.2193	0.2435	0.2207	0.2159	0.2345	0.2201	0.2115	0.1867	0.1143	0.1391	0.2629	0.208
leakland	0.4576	0.33	0.3922	0.2809	0.2949	0.3491	0.3047	0.356	0.424	0.4073	0.3645	0.3809	0.4024	0.4518	0.4283	0.4183	0.4342	0.3772	0.4362	0.3521	0.3431	0.3975	0.3479	0.3068	0.4482	0.4255	0.246	0.3034	0.4153	0.3666
provident	0.4962	0.4162	0.4555	0.3472	0.3762	0.3617	0.3476	0.4268	0.3934	0.4667	0.3977	0.3437	0.3895	0.5458	0.464	0.4896	0.4519	0.4055	0.5191	0.3916	0.411	0.3939	0.5826	0.4097	0.4674	0.3654	0.2577	0.2192	0.5416	0.4836
valley	0.4554	0.4364	0.4924	0.3541	0.4354	0.3542	0.3497	0.426	0.3622	0.4131	0.3781	0.3127	0.344	0.4931	0.4854	0.4709	0.4081	0.3663	0.5143	0.3494	0.3339	0.3652	0.492	0.4512	0.4889	0.3558	0.228	0.2366	0.5365	0.4597
bankofamerica	0.5029	0.4247	0.6092	0.3437	0.4222	0.582	0.4846	0.5861	0.4518	0.5769	0.4811	0.3479	0.4061	0.5253	0.4898	0.482	0.4441	0.3852	0.4736	0.3693	0.3027	0.44	0.3652	0.4737	0.4436	0.3919	0.3085	0.2948	0.4251	0.4282
bbnt	0.5433	0.4809	0.6584	0.3583	0.4515	0.4804	0.4343	0.5721	0.4591	0.6403	0.5105	0.3447	0.3886	0.5484	0.5172	0.5476	0.4647	0.3982	0.535	0.3641	0.3283	0.4896	0.4333	0.4309	0.4645	0.3546	0.283	0.2773	0.5638	0.505
firstcitizen	0.3172	0.3155	0.3795	0.2618	0.2845	0.3219	0.2776	0.3689	0.2663	0.3491	0.2969	0.2109	0.2555	0.377	0.3426	0.3456	0.33	0.3292	0.3587	0.2809	0.2486	0.2913	0.3207	0.2973	0.352	0.2341	0.1435	0.1813	0.357	0.3472
yadkin	0.289	0.2434	0.2078	0.1262	0.1525	0.2084	0.1409	0.175	0.2761	0.2638	0.3118	0.2581	0.2683	0.3202	0.2594	0.1977	0.194	0.2732	0.2331	0.1636	0.1726	0.3121	0.1577	0.178	0.2425	0.2639	0.1709	0.2329	0.1666	0.1993
fifththird	0.5695	0.4737	0.5975	0.3294	0.4097	0.4795	0.4133	0.4933	0.4488	0.6915	0.5646	0.4151	0.3808	0.5532	0.4737	0.5302	0.4274	0.4153	0.4848	0.3291	0.2928	0.5504	0.363	0.3997	0.4449	0.3533	0.2976	0.2928	0.5124	0.4522
firstdefiance	0.2375	0.2352	0.194	0.1807	0.1934	0.201	0.1959	0.1756	0.2713	0.242	0.242	0.1811	0.2129	0.2488	0.1918	0.2254	0.1947	0.2198	0.2332	0.193	0.1893	0.2417	0.2338	0.2343	0.1779	0.2245	0.1825	0.2227	0.2124	0.1993
huntington	0.5588	0.4196	0.527	0.3469	0.3906	0.4603	0.3595	0.4614	0.4517	0.6026	0.5445	0.382	0.4134	0.5726	0.4668	0.5092	0.427	0.4111	0.4673	0.3191	0.3199	0.5524	0.3398	0.4579	0.4154	0.3792	0.3223	0.3069	0.4948	0.4346
keycorp	0.5431	0.4409	0.6051	0.3374	0.423	0.5036	0.3699	0.4926	0.4268	0.6328	0.536	0.3668	0.4087	0.5539	0.4832	0.4875	0.4305	0.4031	0.4771	0.344	0.2926	0.5208	0.3703	0.4106	0.391	0.3534	0.2803	0.2992	0.474	0.407
northwest	0.3373	0.3417	0.3681	0.2465	0.3714	0.298	0.2911	0.3378	0.2685	0.3131	0.2507	0.2774	0.3095	0.3713	0.3444	0.3661	0.3699	0.3235	0.3623	0.3617	0.2714	0.2903	0.4064	0.3261	0.393	0.2812	0.1699	0.1658	0.4012	0.3336
fulton	0.5483	0.4491	0.5264	0.3614	0.4232	0.4293	0.412	0.4823	0.4186	0.5262	0.4709	0.335	0.3771	0.5884	0.5234	0.54	0.4575	0.4181	0.577	0.3732	0.3677	0.4746	0.4371	0.4332	0.4881	0.3781	0.2559	0.2493	0.5247	0.4919
fnb	0.6153	0.4597	0.5626	0.3543	0.4331	0.4324	0.3717	0.4886	0.4593	0.5214	0.4909	0.3778	0.4283	0.6412	0.5862	0.5711	0.4869	0.4785	0.6505	0.3707	0.3452	0.5598	0.4655	0.4239	0.5097	0.4583	0.2975	0.2789	0.6149	0.5135
pnc	0.4542	0.5013	0.5394	0.3923	0.3871	0.4199	0.4066	0.5114	0.3674	0.5567	0.4121	0.281	0.3508	0.478	0.4704	0.4511	0.3696	0.3773	0.4823	0.3603	0.2701	0.3956	0.3557	0.4366	0.4679	0.3193	0.1665	0.2695	0.4531	0.4223
comerica	0.5324	0.4902	0.5812	0.3899	0.426	0.462	0.4127	0.5465	0.3878	0.5935	0.4885	0.3755	0.3827	0.5576	0.5343	0.5511	0.5024	0.4029	0.5194	0.3652	0.3321	0.496	0.4177	0.4575	0.4481	0.3679	0.2809	0.244	0.5384	0.4752
prosperity	0.4447	0.4295	0.4697	0.3644	0.3941	0.3837	0.3702	0.4457	0.3007	0.449	0.3725	0.288	0.3027	0.4723	0.4337	0.4489	0.3816	0.3254	0.4465	0.3544	0.3383	0.3726	0.3822	0.3748	0.4527	0.3163	0.2072	0.1793	0.495	0.4639
texas	0.3891	0.4307	0.4417	0.3791	0.3733	0.3573	0.3445	0.392	0.3438	0.4202	0.3328	0.2717	0.279	0.4592	0.4332	0.4072	0.3815	0.3343	0.4385	0.3199	0.2615	0.3629	0.3909	0.3812	0.4217	0.3487	0.2525	0.1952	0.459	0.4261
cullenfrost	0.3817	0.424	0.4298	0.3312	0.3725	0.3269	0.3504	0.4192	0.2792	0.4111	0.3031	0.2625	0.2842	0.4245	0.385	0.3883	0.3664	0.3271	0.4586	0.3543	0.2788	0.3444	0.4158	0.3635	0.4236	0.2829	0.1458	0.1444	0.4658	0.4877
capitalone	0.4935	0.4131	0.5536	0.3114	0.3964	0.4276	0.4116	0.4788	0.3675	0.5021	0.407	0.3032	0.3483	0.4928	0.437	0.4777	0.3639	0.3648	0.4126	0.3076	0.2645	0.4138	0.3377	0.4386	0.4134	0.3431	0.244	0.3012	0.4092	0.4026
freddiemac	0.0861	0.0729	0.1228	0.03	0.0273	0.1084	0.1017	0.1421	0.0393	0.0519	0.0299	0.0557	0.0285	0.1012	0.0585	0.0982	0.1218	0.0328	0.0947	0.0457	0.0652	0.0806	0.066	0.0443	0.065	0.0339	0.056	-0.0067	0.1077	0.0726
towne	0.4188	0.3003	0.3149	0.2274	0.2515	0.2325	0.1922	0.2714	0.4018	0.3452	0.3503	0.2986	0.369	0.4155	0.356	0.389	0.3961	0.3657	0.3967	0.2931	0.2526	0.3835	0.2667	0.2592	0.354	0.3228	0.1979	0.2507	0.3357	0.2793
union	0.4461	0.3213	0.3826	0.2121	0.2731	0.2852	0.2212	0.3297	0.4732	0.3854	0.3568	0.3003	0.4572	0.4716	0.4381	0.3957	0.46	0.4075	0.4127	0.3487	0.2882	0.3796	0.2959	0.2811	0.4334	0.3685	0.2366	0.2552	0.401	0.353
premier	0.2491	0.2148	0.247	0.1314	0.213	0.2655	0.1702	0.2217	0.2399	0.2243	0.2314	0.1981	0.225	0.267	0.221	0.267	0.1908	0.2711	0.2261	0.1503	0.1536	0.2593	0.1859	0.2294	0.2066	0.2266	0.2026	0.1986	0.223	0.2194
city	0.4432	0.4089	0.4156	0.2777	0.3344	0.3207	0.3078	0.3862	0.3706	0.4269	0.3446	0.3553	0.3702	0.4677	0.4738	0.4204	0.5283	0.3909	0.4623	0.3953	0.3485	0.399	0.4223	0.3226	0.4715	0.3928	0.2539	0.2474	0.4497	0.4265
wesbanco	0.5083	0.4138	0.4385	0.394	0.3575	0.3611	0.3678	0.4275	0.4674	0.4614	0.3985	0.3186	0.3931	0.5426	0.5535	0.4851	0.5596	0.4979	0.5091	0.436	0.3538	0.4953	0.4164	0.422	0.5273	0.4259	0.2865	0.2798	0.522	0.4346
united	0.5726	0.4321	0.5576	0.3319	0.3969	0.3873	0.357	0.442	0.4553	0.4918	0.4833	0.3946	0.4031	0.5955	0.5499	0.5479	0.5098	0.478	0.6047	0.3521	0.3768	0.5299	0.4964	0.4358	0.5121	0.4447	0.2761	0.2946	0.6196	0.484

	hancock	renasant	onnectone	leakland	provident	valley	nkofamer	bbnt	firstcitizen	yadkin	fifththird	rstdefianc	huntingtor	keycorp	northwest	fulton	fnb	pnc	comerica	prosperity	texas	ullenfrost	capitalone	reddiemac	towne	union	premier	city	wesbanco	united
hancock	1																													
renasant	0.3399	1																												
connectone	0.2066	0.2059	1																											
leakland	0.3389	0.4329	0.2268	1																										
provident	0.4342	0.3813	0.2198	0.4028	1																									
valley	0.4704	0.4112	0.1902	0.3603	0.5153	1																								
bankofamerica	0.3715	0.4621	0.1965	0.3784	0.3953	0.4244	1																							
bbnt	0.4134	0.4503	0.1877	0.3767	0.5034	0.4673	0.5553	1																						
firstcitizen	0.3534	0.3379	0.1738	0.2375	0.3705	0.3772	0.3498	0.3221	1																					
yadkin	0.1676	0.2406	0.1341	0.2689	0.1563	0.2218	0.2657	0.213	0.1878	1																				
fifththird	0.3814	0.4358	0.2079	0.3888	0.4596	0.4253	0.5425	0.6228	0.3485	0.2666	1																			
firstdefiance	0.1506	0.1878	0.237	0.224	0.2234	0.1723	0.2372	0.2214	0.1278	0.1869	0.2369	1																		
huntington	0.375	0.4072	0.1936	0.3774	0.4414	0.4019	0.5382	0.5625	0.352	0.2727	0.6485	0.2625	1																	
keycorp	0.3516	0.3921	0.184	0.3288	0.4669	0.4077	0.5314	0.6055	0.378	0.2502	0.6448	0.2079	0.6354	1																
northwest	0.3032	0.3234	0.2414	0.3042	0.4179	0.3835	0.3198	0.3297	0.3015	0.1311	0.321	0.1946	0.3173	0.2802	1															
fulton	0.4623	0.4525	0.2446	0.3786	0.5522	0.5547	0.5189	0.5482	0.4056	0.2391	0.5394	0.2289	0.5278	0.5084	0.3566	1														
fnb	0.4876	0.497	0.2038	0.4284	0.5328	0.5075	0.4935	0.5751	0.386	0.2697	0.5564	0.1796	0.5687	0.5705	0.3719	0.5915	1													
pnc	0.3741	0.4282	0.1852	0.3661	0.4209	0.4643	0.4736	0.5362	0.3632	0.2221	0.4983	0.2022	0.4737	0.4692	0.3291	0.5125	0.4921	1												
comerica	0.4681	0.4469	0.2113	0.3648	0.4688	0.5099	0.5256	0.6158	0.3959	0.2162	0.5808	0.2052	0.5466	0.6079	0.324	0.5728	0.5634	0.5186	1											
prosperity	0.4636	0.3626	0.1765	0.3109	0.451	0.4896	0.3999	0.4869	0.3947	0.1894	0.4886	0.1356	0.409	0.4151	0.3188	0.4947	0.4629	0.4685	0.4935	1										
texas	0.4723	0.392	0.1958	0.336	0.3682	0.4451	0.4278	0.4434	0.3625	0.2008	0.4301	0.2078	0.402	0.3785	0.318	0.436	0.4756	0.4358	0.4628	0.5222	1									
cullenfrost	0.4997	0.3289	0.2323	0.2706	0.4925	0.4566	0.3449	0.4239	0.3559	0.1353	0.3895	0.1646	0.3438	0.3694	0.3657	0.4567	0.4371	0.4095	0.4823	0.5455	0.4473	1								
capitalone	0.3765	0.4284	0.173	0.3318	0.3774	0.4357	0.5319	0.4951	0.3007	0.225	0.471	0.1959	0.4621	0.4903	0.2703	0.4613	0.4637	0.4407	0.4622	0.3856	0.3741	0.3088	1							
freddiemac	0.1149	0.0667	0.0172	0.0528	0.0569	0.0771	0.1115	0.1136	0.0594	0.0053	0.0986	-0.0056	0.0625	0.0695	0.0381	0.0947	0.0946	0.0305	0.1475	0.1215	0.0785	0.1062	0.0678	1						
towne	0.277	0.3815	0.1739	0.3991	0.3049	0.295	0.326	0.335	0.2659	0.243	0.3611	0.215	0.3474	0.3236	0.2168	0.3625	0.3767	0.3042	0.3534	0.272	0.2756	0.2415	0.2978	0.0202	1					
union	0.3258	0.4226	0.1472	0.4007	0.3655	0.342	0.3422	0.406	0.2614	0.2497	0.3635	0.2001	0.3564	0.363	0.278	0.3563	0.4531	0.3478	0.3433	0.2792	0.2889	0.2531	0.3305	0.0215	0.3673	1				
premier	0.2146	0.2402	0.0893	0.2256	0.1802	0.2226	0.2521	0.2361	0.21	0.1929	0.233	0.191	0.2457	0.2212	0.1795	0.2091	0.2878	0.2112	0.1853	0.1545	0.1865	0.1645	0.2126	0.0139	0.1806	0.2595	1			
city	0.4233	0.4074	0.2418	0.4027	0.4317	0.406	0.3747	0.4032	0.3474	0.2206	0.3783	0.2025	0.3732	0.3589	0.3329	0.449	0.4773	0.3783	0.4444	0.398	0.3558	0.4416	0.3549	0.0769	0.3575	0.3884	0.1855	1		
wesbanco	0.4455	0.4544	0.223	0.4778	0.4633	0.4589	0.4189	0.4403	0.3468	0.2286	0.4131	0.2177	0.4351	0.406	0.3585	0.4844	0.548	0.434	0.5227	0.4109	0.4478	0.3842	0.3882	0.094	0.3871	0.425	0.2138	0.516	1	
united	0.5106	0.5104	0.2229	0.45	0.5145	0.5646	0.4647	0.5601	0.4025	0.2479	0.5498	0.1871	0.5195	0.4893	0.3442	0.6017	0.7055	0.4726	0.5191	0.519	0.4738	0.4607	0.4632	0.1097	0.3928	0.4352	0.2654	0.4769	0.5335	1

6.3.2. Distance to inefficiency contagion

The distance to inefficiency contagion outcomes display a similar spillover pattern to the earlier measures. Overall, these outcomes provide some indication of home state bias in both receiving and communicating shocks for all the banks in the sample. The MLM results are provided in Table 6.3.2.1 and the correlation results in Table 6.3.2.2. The results clearly show that DI displays less contagion than DD. Some banks – Ameris Bancorp, Suntrust, Wintrust and MB Financial – experience a very high degree of contagion from their peers, while others – Citi, Towne, Enterprise and First Citizen – are highly resistant. Conversely, some banks – Synovus, Flagstar and Prosperity – display a high ability to transmit shocks, and others – SVB, Keycorp, Northeast Bancshares and Huntington Bancshares – very limited capacity.

Looking at the position of first bracket GSIB banks Table 6.3.2.1, as with DD the GSIB banks do not demonstrate particularly high outcomes in terms of either receiving or transmitting efficiency shocks. Citi group was one of the least affected banks in this category. Only three banks from the sample – Cathey, JP Morgan and Capital One –transmitted their shocks to Citi. Citi, on the other hand, transferred its value shocks to number of banks, including Cathey, Mellon, MB Financial, Wintrust etc. The only other fourth bracket GSIB bank, JP Morgan, transmitted their shocks to only four banks – Flagstar, BBNT, First Citizen and Texas Capital (two of which are from North Carolina).

Table 6.3.2.1- DI Contagion

	cathey	svb	wells	charles	mellon	citi	goldman	jpmorgan	ameris	suntrust	synovus	unitedcon	firstbusey	firstmidw	mb	wintrust	1stsource	firstmerch	oldnation	leaklandir	berkshire	bostonpri	brookline	statestree	chemical	enterprise	flagstar	independ	trustmark	bancorpsc
cathey			0.007			0.015			0.039																		0.005			
svb									0.009	0.008							0					0.022			0.035					
wells							0.026			0.02	0.001																			
charles												0.005									0.032									
mellon																														
citi	0.012				0.006										0.006	0.012		0.005									0			
goldman			0.007								0.007			0.03																0.024
jpmorgan			0.001			0.005																								0.036
ameris										0.001	0.001		0.001	0	0.011			0.045				0.03								
suntrust																							0.021							
synovus	0.01		0.013						0.012	0.041		0.004				0.005		0.002				0.001			0.015					0
unitedcommunity		0.013								0	0.003			0		0.012						0.004						0.005		
firstbusey					0.002																0.044		0.044					0.031		
firstmidwest		0.039			0.007		0.009			0.004		0.033			0															
mb					0																			0						
wintrust																														0.024
1stsource															0.049	0.033														
firstmerchants																								0.021				0.013	0.01	
oldnational													0.033								0.038				0.026					
leaklandindiana																								0.017				0.009	0.022	
berkshire													0.002	0.008				0.026					0.029							
bostonprivate							0.049												0.021											
brookline																														
statestreet				0.021									0.038							0.012										
chemical				0.034	0.001														0.041											
enterprise		0.002	0.044											0.019		0.012						0.047		0.013				0.01		
flagstar	0				0.049			0	0.011	0.039		0.004						0.04			0.023	0.017	0.029			0.004			0	
independent	0.037													0.026		0.044					0.001	0.007							0.031	
trustmark							0.009												0.035											
bancorpsouth															0.036		0.049			0.016					0.039					
hancock																							0.016						0.041	
renasant														0.011				0.011												
connectone																														
leakland																0.02														
provident									0.003								0.018			0.022			0.017					0.025		
valley					0.003										0.023			0.017		0.027			0					0.011		
bankofamerica																0.038														
bbnt								0.016								0.001	0.005	0.029	0.029					0.019					0.007	0.005
firstcitizen				0.049				0.019			0.02																			
yadkin										0.018		0.033	0.04										0.004	0.026					0.029	
fifththird																														
firstdefiance							0.022		0.025															0.004			0.001			
huntington																					0.004									
keycorp											0.001																			
northwest					0.013								0.029																	
fulton									0.026	0.049							0.029	0												
fnb		0.034								0.005												0.012		0.002						
pnc																														
comerica															0.043												0.036			
prosperity	0.02		0				0.031			0	0.003				0.003	0.001			0.004			0								
texas					0.026			0.048	0.039														0.009			0.009				
cullenfrost					0.003																		0.022	0.023						0.049
capitalone		0.016				0.026												0.019												
freddiemac		0.019		0.008	0.023				0.026	0.019	0.027		0.023			0.018		0.001				0.007	0.025		0.028	0.014				
towne							0.033																							
union		0.031									0.036							0.025		0.04										
premier					0.038					0					0.002	0.016												0.042		
city														0.013																
wesbanco									0.017					0.01									0.014				0.006		0.006	
united	0.002			0.019	0.004								0.047											0.002						

	hancock	renasant	connector	leakland	provident	valley	bankofam	bbnt	firstcitizer	yadkin	fifththird	firstdefiar	huntingto	keycorp	northwest	fulton	fnb	pnc	comerica	prosperity	texas	cullenfros	capitalone	freddiema	towne	union	premier	city	wesbanco	united
cathey						0.044									0.005					0.002	0.037									
svb																														
wells																														
charles									0.048															0.01						
mellon					0.005						0.045										0.038									
citi		0.046										0.03	0.019	0.003						0.011										0.039
goldman																		0.048				0.031	0.018				0.025			
jpmorgan							0.025																							
ameris		0.016		0.044			0.037						0.017													0.039	0.045			
suntrust																								0.021						
synovus													0.001	0.004							0.019		0.032						0	0.004
unitedcommunity	0.049									0.035	0.012														0.017					
firstbusey					0.011												0.042								0.034					
firstmidwest																		0.017					0.034			0.011				
mb	0.02										0.029						0.024													
wintrust										0.013																				
1stsource										0.029						0.009														
firstmerchants																							0.001							
oldnational																0.038						0.046								
leaklandindiana			0.021																					0.004			0.002			
berkshire													0.028																	
bostonprivate			0.019	0.009										0.03																
brookline					0.028	0.001																								
statestreet					0.048		0.002																					0.029	0.001	
chemical							0.01			0.009																				
enterprise				0.001			0.014										0.004	0.015										0.021		
flagstar					0.028						0.032	0.002	0.011				0.03						0.04			0.005				
independent				0.036	0.006					0.009									0.02											
trustmark																0.011		0.02				0.001		0.016						
bancorpsouth		0.043																		0.039		0.02								
hancock		0.023			0.029									0.003	0														0.015	
renasant													0.02																	
connectone		0.003																							0.04					
leakland															0.007					0.01			0.004							
provident	0.011																									0.026		0	0.031	0.001
valley															0.046															
bankofamerica					0.016																									
bbnt																			0.034											
firstcitizen								0.025								0.008							0.04							
yadkin												0.012					0.024													
fifththird		0.029				0.04				0.017			0.006									0.019								
firstdefiance																		0.027												
huntington																						0.027								
keycorp								0												0.026										
northwest																														
fulton											0.023																			0.006
fnb			0.021																								0.006			
pnc						0.025																	0.012							
comerica																										0.013				
prosperity	0	0.017		0.01			0.042	0.011			0.007		0.006			0	0.02	0.032	0.008		0.006	0.005	0			0.023	0.045	0.001	0.001	0.012
texas																0.027														
cullenfrost									0.007											0.019								0.02		
capitalone	0.028																											0.012		
freddiemac							0.009			0.001					0.037			0.028								0.004	0.008		0.045	
towne			0.02																											
union									0.024								0.042													
premier												0.006	0.004																	
city																			0.03											
wesbanco	0.014		0.024		0.014	0.04						0.038																		0.036
united		0.025				0.001		0.017		0.015				0.045			0.019											0.04		

Table 6.3.2.2- DI Correlation

	cathey	svb	wells	charles	mellon	citi	goldman	jpmorgan	ameris	suntrust	synovus	edcommu	firstbusey	rstmidwes	mb	wintrust	1stsource	stmerchan	ldnationa	klandindia	berkshire	ostonpriva	brookline	statestree	chemical	enterprise	flagstar	depender	trustmark	ancorpsout
cathey	1																													
svb	0.4138	1																												
wells	0.5171	0.4097	1																											
charles	0.2463	0.3614	0.2613	1																										
mellon	0.3685	0.3852	0.4442	0.4133	1																									
citi	0.4437	0.3378	0.4377	0.2829	0.3988	1																								
goldman	0.2996	0.2741	0.3399	0.347	0.3737	0.4373	1																							
jpmorgan	0.4691	0.3922	0.5678	0.3186	0.4551	0.5243	0.5349	1																						
ameris	0.4758	0.2955	0.3953	0.2157	0.3164	0.3654	0.3061	0.4004	1																					
suntrust	0.5528	0.4339	0.534	0.2774	0.4077	0.4369	0.2988	0.468	0.408	1																				
synovus	0.5169	0.3689	0.4388	0.2194	0.3412	0.3645	0.2389	0.3939	0.3785	0.5818	1																			
unitedcommunity	0.3905	0.223	0.3172	0.1372	0.234	0.2907	0.1815	0.2736	0.2815	0.4133	0.4265	1																		
firstbusey	0.4044	0.3063	0.3686	0.1838	0.336	0.2856	0.2007	0.3093	0.3696	0.388	0.3842	0.296	1																	
firstmidwest	0.5489	0.3988	0.5098	0.2681	0.408	0.3714	0.2983	0.4182	0.3919	0.5824	0.4981	0.3991	0.4277	1																
mb	0.4995	0.4321	0.4567	0.2349	0.3812	0.3794	0.2954	0.421	0.4314	0.4991	0.4195	0.3354	0.4177	0.537	1															
wintrust	0.5541	0.3619	0.4667	0.2164	0.3589	0.3925	0.3088	0.4516	0.3776	0.5119	0.4394	0.3505	0.3607	0.5253	0.4589	1														
1stsource	0.3885	0.2474	0.3224	0.1468	0.2574	0.2793	0.2481	0.3282	0.4333	0.3572	0.3307	0.2806	0.3328	0.3598	0.3516	0.4054	1													
firstmerchants	0.4675	0.3612	0.3838	0.2462	0.3588	0.3445	0.2721	0.3981	0.4338	0.4479	0.4	0.3439	0.3672	0.4796	0.4238	0.4528	0.4189	1												
oldnational	0.4525	0.3477	0.4429	0.2645	0.3776	0.3153	0.3219	0.4637	0.416	0.4134	0.3759	0.3266	0.3311	0.5282	0.455	0.4677	0.3595	0.4967	1											
leaklandindiana	0.2712	0.213	0.2444	0.1772	0.2177	0.2214	0.2363	0.2797	0.332	0.2355	0.1897	0.2078	0.2918	0.3234	0.275	0.2732	0.4224	0.311	0.3207	1										
berkshire	0.3247	0.2168	0.284	0.1577	0.2511	0.2113	0.1477	0.2144	0.2365	0.282	0.2502	0.2034	0.2889	0.3096	0.2961	0.2733	0.3017	0.3063	0.3603	0.2123	1									
bostonprivate	0.5077	0.3564	0.4453	0.2599	0.368	0.3787	0.3164	0.4249	0.3843	0.4854	0.4748	0.3742	0.3518	0.5133	0.5022	0.4616	0.3736	0.4406	0.4615	0.2584	0.2717	1								
brookline	0.2687	0.2522	0.2448	0.2546	0.31	0.1743	0.1968	0.1991	0.1909	0.1824	0.2069	0.1172	0.2269	0.2261	0.2429	0.2327	0.1862	0.2477	0.2863	0.1398	0.2191	0.2325	1							
statestreet	0.3645	0.4126	0.4703	0.4171	0.5172	0.4165	0.3718	0.4895	0.3351	0.4137	0.3641	0.2767	0.3415	0.456	0.3983	0.3484	0.2649	0.3431	0.4031	0.2261	0.2102	0.3502	0.2693	1						
chemical	0.3948	0.3635	0.4032	0.2592	0.2996	0.3347	0.3066	0.387	0.3689	0.3692	0.3258	0.2553	0.3052	0.413	0.4258	0.4274	0.4749	0.4358	0.4556	0.3617	0.3053	0.3756	0.2854	0.3526	1					
enterprise	0.4317	0.3577	0.3797	0.2287	0.295	0.3256	0.3024	0.3507	0.4125	0.4051	0.3786	0.3023	0.3609	0.3944	0.3647	0.3581	0.4373	0.4145	0.3604	0.2815	0.2823	0.385	0.2421	0.348	0.3669	1				
flagstar	0.3091	0.1316	0.1897	0.0769	0.1468	0.309	0.1994	0.2652	0.287	0.2481	0.2354	0.2367	0.1335	0.2218	0.2367	0.2377	0.236	0.2658	0.2166	0.1758	0.197	0.2774	0.1123	0.1434	0.2215	0.2401	1			
independent	0.3768	0.2387	0.2686	0.1756	0.2078	0.2681	0.2087	0.2799	0.2773	0.3099	0.3268	0.3336	0.189	0.34	0.2707	0.3223	0.2465	0.2764	0.2662	0.1683	0.2005	0.3415	0.1415	0.2588	0.2213	0.2688	0.2413	1		
trustmark	0.4531	0.359	0.4222	0.2714	0.3305	0.3024	0.2954	0.3725	0.3326	0.3913	0.3623	0.2585	0.3371	0.4358	0.3869	0.4212	0.3745	0.3724	0.4751	0.3616	0.3352	0.4284	0.3378	0.3539	0.4076	0.3419	0.2286	0.2886	1	
bancorpsouth	0.3954	0.3782	0.3727	0.2728	0.3617	0.3531	0.3127	0.3938	0.3103	0.3955	0.3804	0.2952	0.3268	0.4621	0.4097	0.4057	0.3002	0.3772	0.3861	0.2427	0.261	0.3678	0.2941	0.3771	0.3697	0.3379	0.227	0.2087	0.4058	1
hancock	0.3998	0.3532	0.3481	0.264	0.3523	0.2923	0.278	0.3513	0.28	0.358	0.2907	0.2828	0.2654	0.4027	0.4241	0.3971	0.3019	0.3577	0.4087	0.2341	0.3039	0.3455	0.2669	0.3803	0.4052	0.3078	0.1865	0.2423	0.3861	0.3902
renasant	0.4226	0.3856	0.3707	0.2278	0.2855	0.3574	0.317	0.3865	0.4407	0.396	0.322	0.2645	0.3866	0.3942	0.4381	0.3425	0.3937	0.3621	0.3811	0.3212	0.2922	0.3645	0.214	0.3484	0.4129	0.4052	0.204	0.2215	0.3574	0.3421
connectone	0.1642	0.1741	0.1741	0.115	0.169	0.1079	0.126	0.132	0.0963	0.141	0.1544	0.1469	0.1766	0.1836	0.1781	0.1415	0.1437	0.1387	0.2024	0.128	0.1693	0.1643	0.1975	0.186	0.1577	0.1656	0.08	0.0914	0.2078	0.1555
leakland	0.4714	0.2844	0.3516	0.2204	0.3002	0.3421	0.2904	0.3669	0.41	0.3888	0.3516	0.3224	0.3497	0.4041	0.3732	0.3559	0.409	0.4099	0.3899	0.343	0.3248	0.3605	0.2502	0.2903	0.3973	0.4301	0.2567	0.2562	0.3246	0.304
provident	0.4493	0.3458	0.369	0.2889	0.3344	0.2933	0.2639	0.3658	0.3416	0.3669	0.359	0.2706	0.3824	0.4261	0.3968	0.4067	0.3089	0.3867	0.452	0.2849	0.399	0.3613	0.3731	0.3525	0.3879	0.3605	0.2075	0.258	0.395	0.3166
valley	0.363	0.3341	0.4035	0.2403	0.3289	0.2762	0.2567	0.3533	0.2659	0.3005	0.2861	0.2473	0.3101	0.3789	0.368	0.349	0.2387	0.3442	0.4084	0.2197	0.2722	0.3487	0.3992	0.3497	0.3699	0.3086	0.1454	0.228	0.4435	0.3844
bankofamerica	0.475	0.4335	0.5437	0.3075	0.4196	0.5718	0.3857	0.5389	0.3983	0.5967	0.4424	0.3383	0.3526	0.5288	0.4608	0.4269	0.3341	0.3956	0.3756	0.2098	0.1847	0.4253	0.204	0.4784	0.3498	0.348	0.2517	0.2931	0.3394	0.4071
bbnt	0.5249	0.4505	0.5974	0.2967	0.4055	0.4158	0.3588	0.5091	0.4025	0.5695	0.4343	0.3273	0.3664	0.5132	0.514	0.4837	0.3484	0.4093	0.4617	0.2905	0.2524	0.4741	0.202	0.4153	0.4343	0.356	0.2093	0.2916	0.4422	0.3918
firstcitizen	0.2906	0.2178	0.2648	0.1789	0.213	0.2464	0.2104	0.2725	0.2818	0.2613	0.22	0.1761	0.198	0.2893	0.2503	0.2768	0.2397	0.2921	0.3288	0.2294	0.1821	0.2592	0.1953	0.2857	0.3093	0.2112	0.1776	0.176	0.2967	0.2282
yadkin	0.2411	0.2261	0.1998	0.1484	0.2058	0.1818	0.1066	0.1584	0.2302	0.2941	0.2936	0.2637	0.2696	0.3214	0.261	0.2002	0.1415	0.239	0.2317	0.1135	0.1813	0.2716	0.1619	0.2356	0.1911	0.2672	0.1127	0.2002	0.2051	0.1903
fifththird	0.5685	0.4303	0.5508	0.2468	0.3474	0.45	0.2979	0.4503	0.3942	0.597	0.5065	0.3861	0.3282	0.4937	0.4483	0.5119	0.3491	0.4303	0.4098	0.2585	0.2632	0.5191	0.2063	0.371	0.3909	0.3555	0.2801	0.3007	0.4462	0.3973
firstdefiance	0.275	0.2309	0.192	0.1228	0.1791	0.204	0.1819	0.1963	0.2258	0.2868	0.2512	0.2175	0.2515	0.2629	0.2153	0.2713	0.1896	0.2422	0.2249	0.1798	0.1501	0.2354	0.1325	0.2928	0.1494	0.2279	0.1594	0.2156	0.1951	0.2212
huntington	0.5472	0.3532	0.4954	0.244	0.3607	0.4759	0.3349	0.4563	0.417	0.5916	0.5152	0.3782	0.3366	0.4998	0.4357	0.4839	0.3509	0.4174	0.4324	0.2575	0.2481	0.4966	0.1989	0.4076	0.3462	0.3796	0.297	0.331	0.4026	0.3306
keycorp	0.5669	0.4282	0.5653	0.2316	0.3853	0.5137	0.3374	0.4856	0.4346	0.6106	0.5075	0.3664	0.3849	0.5163	0.4774	0.5003	0.3811	0.4453	0.4207	0.2797	0.2492	0.4763	0.2087	0.3821	0.3571	0.4028	0.2533	0.3202	0.4209	0.3509
northwest	0.2858	0.2979	0.2631	0.2177	0.3054	0.2581	0.2411	0.2871	0.271	0.2524	0.1916	0.1475	0.3116	0.2812	0.2909	0.3187	0.2414	0.2713	0.2965	0.2407	0.2397	0.238	0.2973	0.2518	0.3622	0.2528	0.1084	0.1088	0.3038	0.2938
fulton	0.5052	0.3951	0.4751	0.2681	0.3824	0.3736	0.3102	0.4034	0.3647	0.4683	0.4084	0.3287	0.3737	0.5302	0.4899	0.5142	0.42	0.4542	0.485	0.2877	0.3044	0.4678	0.2681	0.3825	0.4388	0.3787	0.1712	0.2489	0.4468	0.4018
fnb	0.5284	0.3978	0.4478	0.2231	0.3526	0.3521	0.2684	0.3888	0.4242	0.4907	0.3996	0.3169	0.358	0.5288	0.5267	0.4792	0.3918	0.4727	0.5344	0.2825	0.325	0.5114	0.2972	0.3892	0.4518	0.4037	0.2252	0.2699	0.4761	0.4099
pnc	0.4516	0.4922	0.5658	0.3069	0.3601	0.4115	0.3455	0.4826	0.3456	0.5008	0.369	0.2728	0.3389	0.4791	0.4344	0.4591	0.3362	0.4059	0.443	0.2356	0.2749	0.4183	0.1994	0.4883	0.4107	0.3654	0.1524	0.2754	0.4242	0.3741
comerica	0.5019	0.388	0.5099	0.3111	0.3952	0.4257	0.3845	0.5011	0.3936	0.5036	0.4302	0.3217	0.3323	0.4772	0.4615	0.5432	0.394	0.4303	0.4234	0.2844	0.2553	0.4893	0.2424	0.4144	0.4205	0.3246	0.2262	0.291	0.4337	0.4256
prosperity	0.3572	0.3372	0.3991	0.2183	0.2459	0.2907	0.2678	0.3141	0.2806	0.3433	0.2763	0.1963	0.257	0.3418	0.3409	0.3805	0.2683	0.2877	0.3675	0.2778	0.3218	0.3382	0.2374	0.2801	0.3861	0.2589	0.1489	0.1723	0.4324	0.368
texas	0.3874	0.3393	0.3903	0.225	0.2862	0.3461	0.2939	0.4017	0.3062	0.3566	0.3014	0.2663	0.2532	0.3711	0.3994	0.3832	0.3259	0.3776	0.391	0.2566	0.2201	0.3647	0.1811	0.3427	0.3481	0.2772	0.2093	0.2091	0.3767	0.3507
cullenfrost	0.2684	0.3639	0.3216	0.3352	0.3876	0.248	0.241	0.2933	0.2475	0.2997	0.2192	0.1676	0.3157	0.3144	0.3267	0.2933	0.2396	0.2612	0.3276	0.3012	0.3012	0.2748	0.3458	0.3248	0.3063	0.2087	0.0794	0.132	0.3924	0.3523
capitalone	0.4748	0.3856	0.489	0.2333	0.3318	0.3968	0.329	0.4296	0.3269	0.4522	0.3644	0.2955	0.3285	0.4186	0.429	0.4079	0.3108	0.3417	0.3399	0.22	0.2389	0.3951	0.2152	0.3798	0.3247	0.353	0.2059	0.287	0.3412	0.3336
freddiemac	0.0933	-0.0197	0.0738	-0.0281	0.011	0.1009	0.0786	0.097	0.0842	0.0264	0.0346	0.012	0.0259	0.0549	0.0709	0.0766	0.1208	0.0606	0.084	0.0708	0.0374	0.0271	0.0141	0.0174	0.0564	0.0295	0.0913	0.0274	0.0796	0.0681
towne	0.3514	0.3055	0.2693	0.1347	0.259	0.2355	0.1856	0.2525	0.3025	0.3042	0.2988	0.2748	0.3517	0.3842	0.319	0.3442	0.3339	0.3217	0.3136	0.2506	0.2045	0.3009	0.1998	0.3003	0.3611	0.2974	0.1588	0.2177	0.2748	0.327
union	0.3962	0.3393	0.3349	0.1633	0.2584	0.28	0.2198	0.3379	0.4127	0.3588	0.3412	0.3004	0.3817	0.4192	0.3938	0.3785	0.3743	0.4468	0.4167	0.3348	0.2848	0.3741	0.2114	0.2829	0.3938	0.4151	0.219	0.2575	0.3309	0.3415
premier	0.213	0.2085	0.2511	0.1368	0.1906	0.1974	0.1376	0.1747	0.1804	0.2578	0.2173	0.1824	0.2038	0.2433	0.2384	0.2316	0.1156	0.2631	0.1833	0.133	0.0839	0.2136	0.0861	0.2171	0.1374	0.1711	0.0771	0.1932	0.1754	0.2077
city	0.4008	0.3601	0.4017	0.2665	0.3437	0.2748	0.2747	0.3897	0.3275	0.3649	0.291	0.2584	0.3015	0.3858	0.357	0.4124	0.3509	0.384	0.4698	0.3175	0.2909	0.3316	0.2684	0.3584	0.4487	0.3684	0.1862	0.1889	0.3679	0.3589
wesbanco	0.4373	0.3543	0.3446	0.2285	0.33	0.3278	0.2972	0.397	0.4459	0.3693	0.3453	0.3082	0.3473	0.4212	0.4629	0.4109	0.4759	0.4976	0.4727	0.3745	0.3032	0.4217	0.25	0.3839	0.4311	0.4174	0.2174	0.2686	0.3828	0.3755
united	0.5322	0.4006	0.4217	0.258	0.3373	0.3518	0.3005	0.4032	0.4363	0.4534	0.4024	0.323	0.3639	0.5282	0.5125	0.5033	0.419	0.51	0.5513	0.3023	0.3384	0.4904	0.2647	0.3775	0.4888	0.4033	0.2232	0.2629	0.5255	0.4449
	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60

	hancock	renasant	onnectone	leakland	provident	valley	nkofameri	bbnt	firstcitizen	yadkin	fifththird	rstdefianc	huntington	keycorp	northwest	fulton	fnb	pnc	comerica	prosperity	texas	ullenfrost	capitalone	reddiemac	towne	union	premier	city	wesbanco	united
hancock	1																													
renasant	0.2982	1																												
connectone	0.1731	0.1756	1																											
leakland	0.2857	0.3691	0.1542	1																										
provident	0.3583	0.3511	0.1792	0.3719	1																									
valley	0.3999	0.3402	0.1712	0.2561	0.3942	1																								
bankofamerica	0.3462	0.3809	0.1133	0.3263	0.3122	0.3099	1																							
bbnt	0.3658	0.3984	0.1609	0.3318	0.3773	0.368	0.5388	1																						
firstcitizen	0.2728	0.2398	0.1041	0.2391	0.294	0.2579	0.2368	0.2078	1																					
yadkin	0.1682	0.1996	0.1064	0.2367	0.1929	0.1979	0.2254	0.236	0.1055	1																				
fifththird	0.3299	0.3632	0.1653	0.339	0.3655	0.338	0.4922	0.5769	0.2669	0.2349	1																			
firstdefiance	0.1457	0.1809	0.1681	0.2338	0.193	0.1527	0.2247	0.1743	0.1771	0.2276	0.2684	1																		
huntington	0.2911	0.3489	0.1431	0.3695	0.3675	0.3126	0.4944	0.5157	0.2804	0.2254	0.6227	0.259	1																	
keycorp	0.3076	0.3814	0.1262	0.3437	0.3929	0.307	0.5223	0.5734	0.2813	0.2441	0.6482	0.2353	0.6442	1																
northwest	0.221	0.2803	0.1519	0.2821	0.3534	0.2721	0.2453	0.2736	0.2279	0.1249	0.2666	0.1697	0.2333	0.2484	1															
fulton	0.4239	0.4058	0.1478	0.338	0.4404	0.4693	0.4604	0.4567	0.31	0.229	0.4727	0.2144	0.4631	0.47	0.3	1														
fnb	0.4164	0.4447	0.1769	0.3879	0.4333	0.377	0.4107	0.516	0.236	0.2744	0.4685	0.1824	0.467	0.4939	0.3059	0.4868	1													
pnc	0.3721	0.375	0.1417	0.3303	0.3744	0.4016	0.4457	0.5294	0.2652	0.2095	0.5059	0.2297	0.4758	0.4803	0.2976	0.5041	0.4554	1												
comerica	0.3944	0.3676	0.1756	0.3025	0.3843	0.3865	0.4783	0.5847	0.2874	0.2002	0.5398	0.1759	0.484	0.5652	0.2726	0.5289	0.4589	0.4667	1											
prosperity	0.3834	0.3533	0.1576	0.2527	0.3709	0.3729	0.2904	0.3955	0.3242	0.1594	0.3688	0.1354	0.3027	0.3329	0.2751	0.4087	0.3724	0.43	0.3935	1										
texas	0.354	0.3652	0.1562	0.3342	0.2938	0.3055	0.3495	0.4135	0.2947	0.1704	0.3914	0.1684	0.3806	0.3726	0.2823	0.3711	0.4004	0.3947	0.4303	0.4074	1									
cullenfrost	0.3623	0.317	0.2374	0.2717	0.315	0.3518	0.2554	0.3321	0.2565	0.1586	0.3054	0.1397	0.2238	0.2664	0.3496	0.2898	0.3343	0.3406	0.3026	0.4594	0.3202	1								
capitalone	0.2838	0.3346	0.1313	0.2953	0.3264	0.3524	0.4453	0.4472	0.2167	0.2206	0.4531	0.2117	0.4316	0.4751	0.2046	0.4335	0.4115	0.4642	0.4146	0.3267	0.3368	0.2103	1							
freddiemac	0.0442	0.0609	-0.0078	0.0505	0.0679	0.0396	0.0521	0.0687	0.0843	-0.0392	0.0747	0.0225	0.0877	0.064	0.0414	0.0946	0.0594	0.0446	0.1059	0.0692	0.1111	-0.0077	0.0497	1						
towne	0.2609	0.3212	0.0837	0.3339	0.295	0.2278	0.2854	0.261	0.2342	0.2241	0.2683	0.2482	0.246	0.2843	0.2631	0.3231	0.3232	0.2841	0.3083	0.1909	0.2031	0.1729	0.2634	0.0484	1					
union	0.295	0.3696	0.1403	0.3704	0.3448	0.2743	0.3227	0.3554	0.2365	0.2239	0.3281	0.2069	0.3449	0.34	0.2297	0.3654	0.3925	0.3318	0.3327	0.2756	0.2973	0.1928	0.3104	0.0391	0.3178	1				
premier	0.1559	0.1658	0.0832	0.1573	0.1325	0.1712	0.2393	0.1996	0.1309	0.1328	0.2045	0.1905	0.2243	0.2219	0.1292	0.1551	0.2066	0.1979	0.1837	0.1528	0.13	0.1649	0.19	-0.0383	0.1347	0.2208	1			
city	0.4028	0.3573	0.17	0.3735	0.3348	0.3593	0.3323	0.3624	0.3035	0.1677	0.349	0.196	0.3092	0.3212	0.2961	0.4069	0.4168	0.3603	0.3746	0.3741	0.331	0.3192	0.2837	0.0516	0.3179	0.3589	0.1749	1		
wesbanco	0.3643	0.4542	0.1143	0.443	0.4081	0.3368	0.3469	0.4006	0.3114	0.2347	0.3692	0.2254	0.3607	0.3787	0.3231	0.4311	0.4835	0.3992	0.4188	0.3879	0.4351	0.3044	0.3538	0.0729	0.3336	0.4628	0.1836	0.4232	1	
united	0.4677	0.4636	0.1667	0.4073	0.4294	0.4454	0.3963	0.4829	0.3116	0.2427	0.497	0.2249	0.4242	0.4423	0.3134	0.5318	0.5978	0.454	0.4829	0.4461	0.4358	0.3854	0.3707	0.084	0.3843	0.4254	0.2093	0.5104	0.5057	1

6.3.3. Distance to capital contagion

The distance to capital contagion outcomes display broadly similar patterns to the previous two distance to risk measures. Contagion outcomes and the correlation results are provided at Table 6.3.3.1 and Table 6.3.3.2 respectively. The overall result displays a strong association between the US banks, similar to distance to inefficiency but less than distance to default. Some banks are more affected by systemic risk spillover (e.g. Wells Fargo, First Midwest, Wintrust, First Source) whereas others are relatively immune (e.g. Mellon, Independent, Provident). In terms of transmitting shocks to other banks, three banks are ahead of the sample – Fulton, Hancock and Suntrust. Conversely, some banks – Citi, Fifth Third, Keycorp, Charles, Wells Fargo and Cathey – transmitted few shocks to their peers. One bank in the sample, Provident Financial Corp, did not transmit any shocks to any bank.

Of the major GSIB banks (4^{th} bracket), six transmitted their shocks to Citi – JP Morgan, First Bushy, First Mid-West, MB Financial, FNB and Premier. An interesting fact is that half of them are from the state of Illinois, suggesting the financial health of Citi is directly affected by the financial health of Illinois. Citi, on the other hand, transmitted shocks to only two other banks, United Community and Premier. JP Morgan transmitted its capital shocks to five banks – Citi, SVP, Charles, Lakeland and Premier, while receiving shocks from Mellon, Independent, Hancock, Keycorp, Freddie Mac, Premier and City.

Table 6.3.3.1- DC Contagion

	cathey	svb	wells	charles	mellon	citi	goldman	jpmorgan	ameris	suntrust	synovus	unitedcon	firstbusey	firstmidw	mb	wintrust	1stsource	firstmerch	oldnation	leaklandin	berkshire	bostonpri	brookline	statestree	chemical	enterprise	flagstar	independ	trustmark	bancorpso
cathey			0.022																											
svb									0.001											0.025									0.008	
wells																														
charles							0.02								0.023					0.003	0.005				0.026					
mellon	0.022							0.001						0.004			0.016			0.004					0.031					
citi												0.006																		
goldman																0.033			0.001						0.01				0.045	0.038
jpmorgan		0.049		0.039		0.007														0.014										
ameris																														
suntrust				0.009							0.004							0.005							0.001		0.028			0.028
synovus									0.045								0.035							0.007						
unitedcommunity	0.003		0.01											0.009		0.047					0									
firstbusey		0.026	0.017			0.017								0.029																
firstmidwest	0.001		0.004	0.028		0.038											0.005	0.045		0.011						0.015	0.044			
mb			0.04			0.037			0.014		0.008						0			0.034					0.003		0.015			
wintrust							0.036			0.019											0.031						0.41			
1stsource																												0.01		
firstmerchants							0.001																0.006						0.002	
oldnational																														
leaklandindiana					0.044							0.002	0.011						0.031											
berkshire														0.016				0.008							0.008					
bostonprivate		0.017																0.012		0.021									0.014	
brookline			0.002										0.043			0.036	0.025	0.012	0.002						0.027				0.034	
statestreet	0.04		0.006							0.003	0.007	0		0.049					0.02											
chemical														0.028																
enterprise																						0.028								
flagstar											0										0.033				0.027					
independent		0.019						0.009									0.008										0.014			
trustmark																	0.015						0.021			0.03				
bancorpsouth		0.028																						0.049						
hancock	0.006		0	0.002			0.001	0.005		0		0.026		0.034	0.013		0.003		0.001										0.008	0.008
renasant		0.015												0.041																
connectone									0.037					0.01		0.047													0.023	
leakland					0.024																			0.022	0.041					
provident																														
valley																														
bankofamerica												0.024					0.041													
bbnt																														
firstcitizen	0.034								0.004																					
yadkin									0.023				0	0.026			0.022													0.002
fifththird																														
firstdefiance																0.011		0.017												
huntington																		0.01												
keycorp								0.035		0.001																				
northwest																														
fulton												0.019				0.034	0.024	0.009	0.025						0.018				0.016	
fnb			0.008	0.012		0.007										0.024						0.044	0.036							0.01
pnc																														
comerica		0.006					0.012									0.002	0.024				0.021		0.017	0.045					0.006	0.006
prosperity																														
texas							0.009																				0.033			0.001
cullenfrost																						0.036					0.041			
capitalone											0.032					0.049	0.001						0.004							
freddiemac								0.042			0.017																	0.002		
towne										0.028																				
union										0.002								0.001												
premier			0.01			0.011	0.003	0	0.006	0.016			0.016	0.021	0.011			0						0.007						
city			0.022	0.04				0.002													0.008	0.004							0.038	
wesbanco																								0.005				0.034		
united			0.011								0.005																			

	hancock	renasant	connector	leakland	provident	valley	bankofam	bbnt	firstcitize	yadkin	fifththird	firstdefian	huntingto	keycorp	northwes	fulton	fnb	pnc	comerica	prosperity	texas	cullenfros	capitalone	freddiema	towne	union	premier	city	wesbanco	united
cathey									0.048					0.039								0.017								
svb		0.014																							0.003				0.011	
wells																									0.045					
charles																		0.02									0.016			
mellon										0.002					0.007							0.006								
citi																											0.044			
goldman								0.026													0.049						0.002			
jpmorgan																											0.021			
ameris																		0.048							0.011		0.04			
suntrust		0	0.044	0.027		0.038		0.001			0.004		0.002	0.005		0.045			0	0.017		0.021								
synovus					0.018									0																
unitedcommunity						0.005					0.044																			
firstbusey			0.003						0.046			0.035	0																	
firstmidwest		0					0.004											0.024			0.04									0.027
mb						0.043		0.014			0.009		0						0.013											
wintrust		0.016				0.049											0.041			0.004		0.02								0.005
1stsource																														
firstmerchants	0.038																			0.04			0.015							
oldnational		0.031											0.03														0.033			
leaklandindiana			0.034			0.004													0.017	0								0.024	0.006	
berkshire																														
bostonprivate		0.016							0.004	0.045																			0.047	
brookline																	0.01							0.017						
statestreet						0.009								0		0.009							0.005					0.026		
chemical		0.018																												
enterprise									0.036								0.022													
flagstar	0.015					0.013	0.015		0.035																					
independent												0.039												0.008						
trustmark								0.036							0.001					0.017	0.016					0.003				
bancorpsouth																														
hancock				0.036		0.005	0.014	0.002	0.004				0.009			0.001		0.014		0	0.002	0.019	0.003		0.013			0.025	0.005	0.001
renasant																														
connectone						0.022																								
leakland									0.022				0.017																	
provident																														
valley																														
bankofamerica														0.035										0.048						
bbnt																						0.049	0.002							
firstcitizen																														
yadkin			0.001	0.022													0			0.036				0.036		0.03			0.025	0.027
fifththird																				0.028										
firstdefiance	0.007																0.044													
huntington																	0.003													
keycorp		0.007	0.002	0.001																										
northwest			0.001						0.035									0.038												
fulton				0.033					0.002								0.021	0.048			0.01							0.002	0.001	0.016
fnb																		0.035			0.007									
pnc									0.013								0.026													
comerica				0.005		0											0.046					0.008				0.022			0.004	
prosperity																										0.017	0.042		0.011	
texas								0.041			0.012		0.009						0.01	0.016		0.039								
cullenfrost							0.034																							
capitalone				0.031							0.004			0.018					0.006									0.008		
freddiemac							0.004			0.021					0.035															
towne	0.026																													
union														0.02																
premier									0.008			0.027		0.011		0.039		0.04				0.019								
city		0.047				0.003									0.021								0.049							
wesbanco																	0.02				0.018								0	
united			0.01			0.023					0			0.002		0.017	0.009		0.035			0						0.045		

Table 6.3.3.2- DC Correlation

	cathey	svb	wells	charles	mellon	citi	goldman	jpmorgan	ameris	suntrust	synovus	edcommu	firstbusey	rstmidwes	mb	wintrust	1stsource	stmerchan	ldnationa	klandindia	berkshire	stonpriva	brookline	statestree	chemical	enterprise	flagstar	depender	trustmark	ancorpsout
cathey	1																													
svb	0.4663	1																												
wells	0.5231	0.4635	1																											
charles	0.4075	0.4348	0.4404	1																										
mellon	0.22	0.2031	0.2391	0.2355	1																									
citi	0.4421	0.3925	0.5368	0.3936	0.2375	1																								
goldman	0.3859	0.3771	0.4421	0.4658	0.337	0.4652	1																							
jpmorgan	0.4365	0.442	0.6043	0.4433	0.3265	0.5177	0.5266	1																						
ameris	0.3926	0.309	0.4044	0.3172	0.1617	0.3736	0.2503	0.3648	1																					
suntrust	0.5465	0.4847	0.6335	0.4365	0.2684	0.5283	0.4202	0.547	0.4237	1																				
synovus	0.4779	0.4275	0.5065	0.2923	0.154	0.4523	0.3018	0.3952	0.3555	0.5789	1																			
unitedcommunity	0.3966	0.3458	0.3729	0.2413	0.1767	0.3383	0.2167	0.2964	0.2793	0.3978	0.3861	1																		
firstbusey	0.4258	0.3448	0.4042	0.2764	0.1827	0.3755	0.2674	0.3527	0.3818	0.4248	0.3726	0.3281	1																	
firstmidwest	0.6086	0.4645	0.5459	0.4022	0.2332	0.4811	0.3733	0.4536	0.4209	0.562	0.5239	0.4101	0.463	1																
mb	0.5618	0.4516	0.4695	0.3623	0.1876	0.387	0.3475	0.4206	0.4177	0.5234	0.4083	0.3622	0.4521	0.5893	1															
wintrust	0.5169	0.426	0.4708	0.2978	0.2186	0.4066	0.2957	0.3896	0.3268	0.5091	0.4351	0.3572	0.355	0.5439	0.4896	1														
1stsource	0.4803	0.392	0.4492	0.3485	0.2392	0.335	0.3118	0.3864	0.4312	0.4418	0.3906	0.3821	0.4042	0.5137	0.4576	0.4655	1													
firstmerchants	0.3789	0.3508	0.3912	0.3283	0.1297	0.2712	0.2823	0.3585	0.3722	0.3896	0.2983	0.2838	0.3352	0.4125	0.4299	0.3562	0.4222	1												
oldnational	0.5307	0.4385	0.5038	0.3772	0.2042	0.3879	0.3247	0.44	0.4205	0.4798	0.4369	0.3856	0.4025	0.5863	0.5044	0.5202	0.4295	0.4349	1											
leaklandindiana	0.3689	0.3127	0.3805	0.3663	0.2598	0.2908	0.3199	0.3273	0.3015	0.3341	0.2568	0.3113	0.353	0.4199	0.3404	0.3053	0.452	0.3927	0.3571	1										
berkshire	0.3529	0.3139	0.3491	0.2846	0.1917	0.2961	0.2581	0.2985	0.298	0.3669	0.3063	0.2428	0.3305	0.3905	0.3416	0.3114	0.3596	0.3163	0.3727	0.2325	1									
bostonprivate	0.5088	0.4146	0.4429	0.3619	0.2007	0.4091	0.3088	0.3724	0.347	0.4631	0.4369	0.398	0.3674	0.5136	0.4617	0.4261	0.4357	0.3909	0.4956	0.3353	0.3324	1								
brookline	0.4367	0.393	0.4201	0.3685	0.1737	0.3597	0.3794	0.3836	0.3446	0.4041	0.3317	0.3093	0.3113	0.476	0.445	0.4616	0.4415	0.3521	0.5034	0.3197	0.3835	0.4177	1							
statestreet	0.4127	0.4071	0.4887	0.4275	0.2768	0.4163	0.4306	0.4295	0.3382	0.4443	0.3677	0.297	0.2793	0.4255	0.404	0.3768	0.3457	0.3105	0.4277	0.2763	0.2631	0.3624	0.3774	1						
chemical	0.4791	0.4314	0.4537	0.3702	0.2602	0.383	0.3495	0.4111	0.3819	0.4617	0.3923	0.3577	0.4069	0.5222	0.4679	0.4464	0.5252	0.4482	0.4661	0.432	0.4334	0.4221	0.4341	0.3788	1					
enterprise	0.3976	0.3472	0.351	0.3613	0.1685	0.2852	0.3031	0.3434	0.3709	0.4045	0.2952	0.2619	0.3445	0.4142	0.4272	0.3277	0.4004	0.3267	0.383	0.358	0.2803	0.3593	0.3409	0.3392	0.3741	1				
flagstar	0.2963	0.2457	0.237	0.2222	0.1168	0.2693	0.175	0.1951	0.2189	0.289	0.3419	0.265	0.2472	0.3247	0.2838	0.2569	0.2555	0.2095	0.2855	0.1679	0.2391	0.3293	0.2438	0.2022	0.2783	0.2265	1			
independent	0.2963	0.2334	0.3021	0.1833	0.1359	0.2516	0.2069	0.2472	0.2781	0.3505	0.3258	0.2701	0.2415	0.3258	0.2339	0.2945	0.206	0.218	0.2689	0.1786	0.2052	0.2753	0.2307	0.2171	0.2393	0.2522	0.2217	1		
trustmark	0.5465	0.4572	0.5148	0.4111	0.2548	0.4055	0.3737	0.4356	0.4303	0.5033	0.4363	0.4031	0.3718	0.5657	0.511	0.4751	0.536	0.4104	0.5826	0.4042	0.391	0.5188	0.5139	0.4152	0.5224	0.4096	0.2565	0.2728	1	
bancorpsouth	0.4997	0.4577	0.4626	0.4034	0.1815	0.3632	0.3679	0.4301	0.3775	0.4789	0.3923	0.307	0.3076	0.5389	0.4723	0.4322	0.4148	0.3842	0.5024	0.3534	0.3005	0.4141	0.4341	0.3742	0.4294	0.3697	0.2362	0.2109	0.5178	1
hancock	0.4949	0.4382	0.4192	0.3696	0.189	0.3373	0.3507	0.3965	0.3166	0.3854	0.3585	0.3349	0.3358	0.4673	0.4643	0.407	0.389	0.3606	0.4817	0.3458	0.3425	0.4171	0.3794	0.3347	0.3995	0.3499	0.242	0.2144	0.4925	0.4509
renasant	0.4439	0.3502	0.4088	0.3212	0.2074	0.4043	0.3233	0.3868	0.3949	0.4649	0.3563	0.309	0.3774	0.4374	0.439	0.3709	0.4238	0.3808	0.4336	0.3143	0.3482	0.389	0.3531	0.3421	0.4969	0.3751	0.2294	0.2433	0.4698	0.3462
connectone	0.1832	0.2055	0.2209	0.2149	0.2087	0.2149	0.2057	0.2189	0.1686	0.2261	0.1703	0.1995	0.1884	0.2048	0.2237	0.2068	0.1877	0.2498	0.2264	0.2054	0.2389	0.2172	0.2206	0.2176	0.2332	0.1839	0.123	0.1111	0.2327	0.1659
leakland	0.3932	0.3186	0.3595	0.291	0.2092	0.3184	0.2737	0.3218	0.3627	0.4001	0.2948	0.302	0.4083	0.4253	0.3606	0.3595	0.4159	0.3369	0.4002	0.3219	0.3323	0.3625	0.3837	0.2931	0.4139	0.3926	0.2063	0.2448	0.401	0.3263
provident	-0.0331	-0.0328	-0.0095	-0.0184	-0.0063	0.0074	-0.0278	-0.0167	-0.0251	-0.0137	0.0395	-0.0079	-0.0074	-0.0241	-0.0247	-0.0016	-0.0362	-0.0211	0.0159	-0.0132	-0.013	-0.0048	-0.0365	0.0294	-0.0414	-0.0176	0.0257	-0.0145	-0.0425	-0.0261
valley	0.4927	0.4595	0.4865	0.3679	0.2194	0.3962	0.3564	0.4323	0.3357	0.4504	0.3898	0.3824	0.328	0.5276	0.4916	0.5005	0.4038	0.3623	0.5223	0.3171	0.3525	0.4194	0.4613	0.4169	0.4549	0.3586	0.2655	0.2293	0.5333	0.4735
bankofamerica	0.4907	0.4681	0.627	0.4015	0.2875	0.5637	0.4524	0.595	0.4347	0.6068	0.5038	0.3691	0.4146	0.5403	0.4782	0.4592	0.4612	0.3581	0.4873	0.3568	0.3305	0.4308	0.4049	0.4681	0.4424	0.3781	0.2765	0.3152	0.4506	0.4555
bbnt	0.5202	0.4704	0.6466	0.4232	0.2338	0.5036	0.3943	0.5354	0.4287	0.674	0.5244	0.3494	0.3913	0.5351	0.5096	0.5191	0.4397	0.3923	0.5238	0.3587	0.3508	0.463	0.4395	0.4325	0.4446	0.3596	0.2654	0.2943	0.5307	0.484
firstcitizen	0.2766	0.2907	0.3198	0.2386	0.1766	0.2783	0.2784	0.3296	0.2422	0.2983	0.2332	0.2112	0.224	0.3122	0.3003	0.2791	0.2706	0.2398	0.2619	0.2704	0.1955	0.2145	0.2305	0.2754	0.28	0.2202	0.0887	0.1253	0.2682	0.328
yadkin	0.2227	0.2425	0.2069	0.1629	0.0911	0.2394	0.152	0.1823	0.2566	0.2436	0.2876	0.2004	0.2626	0.2984	0.2507	0.1765	0.2407	0.2236	0.2188	0.1541	0.155	0.2735	0.1585	0.2184	0.2244	0.2306	0.1653	0.2275	0.1979	0.2529
fifththird	0.5473	0.4677	0.6112	0.3868	0.2459	0.4825	0.419	0.517	0.3818	0.6627	0.5379	0.3776	0.3508	0.5261	0.47	0.4763	0.4406	0.3876	0.4719	0.3341	0.3267	0.4936	0.4107	0.4175	0.4471	0.3438	0.2577	0.315	0.4991	0.4719
firstdefiance	0.1701	0.1445	0.145	0.1912	0.1474	0.1411	0.1771	0.132	0.1912	0.1591	0.1549	0.1548	0.1286	0.1823	0.1656	0.1548	0.1844	0.1392	0.1866	0.1634	0.1642	0.1836	0.223	0.2014	0.1457	0.138	0.1354	0.1737	0.1832	0.1743
huntington	0.5313	0.4625	0.5414	0.411	0.2232	0.5083	0.3489	0.4348	0.3941	0.6037	0.5076	0.3617	0.3962	0.5687	0.4649	0.4524	0.4354	0.3747	0.4793	0.3099	0.3239	0.4886	0.3588	0.4222	0.4481	0.3231	0.2915	0.2909	0.4824	0.4521
keycorp	0.4764	0.4625	0.5933	0.3747	0.2487	0.4907	0.3899	0.5074	0.3384	0.6296	0.5318	0.3692	0.3345	0.5203	0.4376	0.4462	0.4019	0.3529	0.4468	0.3214	0.2924	0.46	0.3625	0.4127	0.4052	0.2891	0.2748	0.2999	0.4573	0.4298
northwest	0.3613	0.3402	0.3473	0.2964	0.2328	0.3294	0.3328	0.3438	0.2894	0.3458	0.2466	0.2977	0.2907	0.3922	0.3661	0.3476	0.3959	0.3204	0.3438	0.3492	0.2666	0.3129	0.403	0.3118	0.4267	0.3169	0.1563	0.1428	0.402	0.3301
fulton	0.5496	0.441	0.5152	0.3754	0.2311	0.4135	0.3626	0.4377	0.3842	0.5412	0.462	0.3652	0.3652	0.5567	0.5373	0.4998	0.4942	0.3748	0.556	0.3208	0.37	0.4597	0.4478	0.4345	0.4777	0.381	0.25	0.251	0.5315	0.4959
fnb	0.5987	0.4814	0.5292	0.3903	0.2273	0.4367	0.3471	0.4476	0.4348	0.5287	0.486	0.4111	0.4096	0.6349	0.5883	0.5079	0.4948	0.4343	0.6132	0.3535	0.3641	0.5424	0.5062	0.4256	0.5083	0.4192	0.3081	0.2683	0.6126	0.5349
pnc	0.4448	0.4955	0.5635	0.4434	0.2641	0.4851	0.434	0.5083	0.3657	0.5727	0.4028	0.297	0.3265	0.4494	0.4346	0.4003	0.3826	0.3452	0.4406	0.3738	0.3005	0.3807	0.3701	0.4302	0.4357	0.3222	0.1956	0.2524	0.4784	0.3979
comerica	0.515	0.4983	0.5787	0.4225	0.2129	0.4469	0.403	0.5128	0.33	0.5719	0.4798	0.3742	0.3283	0.5532	0.4964	0.5186	0.451	0.3929	0.5018	0.3275	0.315	0.4285	0.426	0.4658	0.4663	0.3186	0.2483	0.2452	0.5	0.5055
prosperity	0.4906	0.4505	0.4557	0.3808	0.2117	0.3598	0.3725	0.4464	0.346	0.4532	0.3782	0.3317	0.2891	0.4773	0.4605	0.408	0.4164	0.3082	0.4431	0.358	0.3082	0.3781	0.383	0.3562	0.4138	0.3512	0.2033	0.2138	0.4967	0.4888
texas	0.4088	0.4166	0.4088	0.3802	0.1887	0.3331	0.3364	0.3778	0.3282	0.3998	0.3272	0.2869	0.2575	0.4533	0.4055	0.3664	0.3876	0.3295	0.4422	0.3143	0.2735	0.3626	0.4049	0.3379	0.4127	0.3458	0.2427	0.2125	0.4654	0.4393
cullenfrost	0.4632	0.4832	0.4927	0.389	0.286	0.3945	0.3999	0.4886	0.3506	0.4873	0.3772	0.3045	0.3051	0.511	0.48	0.442	0.4347	0.3259	0.4963	0.3804	0.3411	0.3815	0.4072	0.4156	0.4489	0.3607	0.1951	0.2292	0.483	0.5308
capitalone	0.4666	0.4037	0.5198	0.3446	0.156	0.4541	0.392	0.4473	0.3482	0.5135	0.3916	0.3141	0.3078	0.4921	0.4054	0.4023	0.356	0.3316	0.3971	0.2777	0.292	0.3871	0.3587	0.4355	0.4072	0.3098	0.2538	0.2877	0.4068	0.3989
freddiemac	0.2491	0.1885	0.3205	0.1665	0.0837	0.2866	0.2236	0.29	0.2493	0.3051	0.2905	0.219	0.2749	0.278	0.212	0.2292	0.2152	0.2047	0.2667	0.1429	0.1699	0.2616	0.1998	0.254	0.2153	0.219	0.2111	0.3006	0.2377	0.1946
towne	0.3507	0.26	0.2939	0.2161	0.1162	0.2823	0.1803	0.2128	0.3753	0.3123	0.3273	0.2422	0.3307	0.3533	0.323	0.3228	0.3884	0.3035	0.3347	0.242	0.2227	0.3299	0.257	0.2465	0.331	0.2768	0.2038	0.2314	0.3191	0.2158
union	0.4304	0.3268	0.3586	0.2791	0.143	0.3138	0.2053	0.2839	0.4394	0.3726	0.317	0.2906	0.4337	0.4627	0.4221	0.349	0.4211	0.3728	0.4185	0.341	0.2897	0.3417	0.3429	0.2843	0.421	0.3347	0.2355	0.249	0.4121	0.3462
premier	0.1851	0.1732	0.2106	0.0923	0.0915	0.2181	0.1853	0.1971	0.2127	0.1926	0.1946	0.1018	0.1898	0.2129	0.2195	0.2305	0.1358	0.1619	0.1478	0.107	0.1438	0.2057	0.1708	0.1671	0.157	0.181	0.173	0.1958	0.164	0.1513
city	0.459	0.4516	0.4195	0.3249	0.1982	0.3212	0.3098	0.3859	0.3461	0.4342	0.3614	0.3848	0.3795	0.4808	0.4618	0.4371	0.5003	0.3867	0.4682	0.4057	0.336	0.4224	0.4328	0.3459	0.4874	0.4106	0.2566	0.2208	0.4973	0.4441
wesbanco	0.5157	0.4156	0.4501	0.3995	0.2326	0.3782	0.3508	0.4204	0.4358	0.5065	0.3788	0.3383	0.3969	0.5263	0.5361	0.4452	0.5258	0.4719	0.4891	0.3899	0.358	0.4735	0.4205	0.4436	0.523	0.4115	0.2664	0.2759	0.5131	0.4058
united	0.588	0.4806	0.5501	0.3692	0.1621	0.4024	0.3266	0.4318	0.425	0.4914	0.4868	0.4072	0.4033	0.5758	0.5333	0.5201	0.4986	0.4411	0.6046	0.35	0.3607	0.5128	0.485	0.4195	0.471	0.4049	0.298	0.2739	0.617	0.5069

	hancock	renasant	onnectone	leakland	provident	valley	nkofameri	bbnt	firstcitizen	yadkin	fifththird	rstdefianc	huntingtor	keycorp	northwest	fulton	fnb	pnc	comerica	prosperity	texas	cullenfrost	capitalone	reddiemac	towne	union	premier	city	wesbanco	united
hancock	1																													
renasant	0.3408	1																												
connectone	0.1868	0.2104	1																											
leakland	0.3218	0.371	0.2298	1																										
provident	-0.0352	-0.0461	0.0262	-0.0544	1																									
valley	0.4653	0.3881	0.2006	0.3591	-0.0341	1																								
bankofamerica	0.3799	0.4559	0.1945	0.333	-0.026	0.4615	1																							
bbnt	0.4101	0.4042	0.2055	0.335	-0.0184	0.4769	0.5826	1																						
firstcitizen	0.2583	0.2507	0.1669	0.1951	-0.0326	0.3022	0.306	0.2795	1																					
yadkin	0.1709	0.2525	0.1301	0.2386	-0.0208	0.2225	0.2788	0.2119	0.1733	1																				
fifththird	0.3981	0.4215	0.2228	0.332	-0.0323	0.4609	0.5696	0.6422	0.3277	0.2626	1																			
firstdefiance	0.1012	0.1264	0.1617	0.149	-0.0087	0.1349	0.1877	0.1891	0.1046	0.1541	0.1858	1																		
huntington	0.3831	0.4254	0.1748	0.3568	-0.0092	0.4414	0.5165	0.5795	0.3136	0.2786	0.605	0.2229	1																	
keycorp	0.3518	0.3815	0.1559	0.2622	-0.0062	0.419	0.5483	0.6165	0.3293	0.2622	0.6055	0.145	0.595	1																
northwest	0.2816	0.3303	0.2006	0.271	-0.0172	0.3395	0.3438	0.3402	0.2545	0.0992	0.3301	0.1772	0.3156	0.3014	1															
fulton	0.4509	0.4317	0.2381	0.364	-0.0285	0.566	0.5283	0.5265	0.3103	0.2445	0.5271	0.2206	0.4978	0.4774	0.3624	1														
fnb	0.4855	0.4731	0.202	0.4148	-0.0239	0.5187	0.5123	0.5523	0.3035	0.2775	0.5261	0.1638	0.5696	0.5166	0.386	0.5729	1													
pnc	0.3754	0.4145	0.1903	0.3495	-0.0174	0.452	0.5019	0.5397	0.3267	0.1879	0.525	0.1396	0.5039	0.5029	0.358	0.4661	0.4885	1												
comerica	0.4416	0.4082	0.2173	0.2944	-0.0263	0.507	0.5203	0.5922	0.2989	0.2011	0.5669	0.1642	0.5401	0.5762	0.3315	0.5003	0.5346	0.5039	1											
prosperity	0.4712	0.3667	0.179	0.3058	-0.0393	0.4816	0.4152	0.4711	0.3448	0.2152	0.4765	0.1425	0.4257	0.4209	0.3491	0.4886	0.4947	0.4335	0.491	1										
texas	0.4586	0.3657	0.1859	0.3419	-0.0388	0.4499	0.402	0.3959	0.319	0.1984	0.4019	0.1625	0.3873	0.3465	0.3303	0.4101	0.4394	0.419	0.4247	0.488	1									
cullenfrost	0.463	0.3636	0.2247	0.28	-0.031	0.48	0.4494	0.5012	0.3614	0.1843	0.4938	0.1663	0.4488	0.4802	0.3922	0.5036	0.4893	0.4553	0.5503	0.5424	0.4641	1								
capitalone	0.4078	0.4037	0.1851	0.2943	-0.0244	0.4172	0.5223	0.4976	0.2518	0.2239	0.4868	0.1471	0.4475	0.4483	0.2739	0.4321	0.4378	0.4137	0.4382	0.3728	0.3563	0.3755	1							
freddiemac	0.1743	0.2254	0.0853	0.2157	0.0424	0.2465	0.3918	0.3165	0.094	0.2409	0.3006	0.131	0.2949	0.3073	0.1291	0.2767	0.2625	0.1823	0.2625	0.1877	0.1626	0.1698	0.2652	1						
towne	0.2666	0.343	0.138	0.3409	-0.0157	0.3098	0.3121	0.3274	0.1991	0.2662	0.3252	0.1697	0.3054	0.2874	0.2033	0.3554	0.3267	0.2782	0.2746	0.2496	0.2384	0.2435	0.2445	0.1808	1					
union	0.3515	0.389	0.1465	0.358	-0.0113	0.3439	0.3404	0.3697	0.2019	0.2324	0.3437	0.1707	0.3512	0.2917	0.2769	0.3642	0.4031	0.3353	0.319	0.2995	0.2945	0.3043	0.3084	0.1598	0.3745	1				
premier	0.1546	0.21	0.0895	0.1785	-0.0353	0.2014	0.2309	0.1893	0.1844	0.1869	0.2031	0.157	0.187	0.1801	0.1468	0.1826	0.2004	0.1776	0.1441	0.1485	0.1339	0.1433	0.1913	0.1625	0.1361	0.1845	1			
city	0.4453	0.3819	0.2407	0.42	-0.0152	0.456	0.3819	0.411	0.3243	0.2179	0.4256	0.1663	0.399	0.3743	0.3453	0.4706	0.4848	0.4067	0.4517	0.4515	0.3956	0.4489	0.354	0.1698	0.3177	0.4071	0.1787	1		
wesbanco	0.4298	0.4233	0.2526	0.4409	-0.0298	0.4797	0.4218	0.4494	0.2349	0.2538	0.4135	0.1968	0.4338	0.4008	0.3775	0.4785	0.5585	0.4575	0.4868	0.42	0.402	0.4249	0.3872	0.222	0.3575	0.4165	0.1505	0.4992	1	
united	0.5015	0.4849	0.2062	0.4006	-0.0302	0.5534	0.4824	0.548	0.3142	0.248	0.5463	0.1541	0.5087	0.4775	0.3319	0.5857	0.6625	0.4506	0.501	0.5066	0.4636	0.4875	0.4371	0.272	0.3785	0.4221	0.1934	0.469	0.5062	1

6.3.4. Overall contagion

Generally, the contagion risk analysis across three different distance to risk measures (default, inefficiency and capital) in this chapter reveals an evenly distributed but detectable level of contagion between the US banks. Minor banks both transmit and receive more value shocks than their larger counterparts, while larger banks are more resistant to shock than their smaller colleagues in all three distance to risk measures. In this regard, there was no evidence of any superiority of GSIB banks. Two of the largest US banks, Citi and JP Morgan, are least active in the DD and DI measures. Distance to default produces the highest level of contagion compared to DI and DC. The results are consistent across the different distance to risk measures, which validates the outcomes of the previous chapters.

6.4. Conclusion

This chapter showed the contagion risk for sixty US banks using three different distance to risk procedures (distance to default, distance to inefficiency and distance to capital). Extreme shocks for US banks were modelled as a function of extreme shocks confronted by other banks in the sample. The probability of these shocks moving through the sample was then calculated by using multinomial logistic regression analysis.

In general, the findings from all three assorted distance to risk measures showed a strong association between US banks. The outcomes also indicated that minor banks transmit and receive a higher number of shocks than their larger counterparts, while the bigger banks display more resistance to shock than their smaller colleagues in all three different distance to risk measures. There was no evidence of superiority of

GSIB banks. Two of the largest US banks, Citi and JP Morgan, were less active compared to the other banks. Perhaps the most important observation was the minimal amount of state bias in contagion risk across the different distance to risk measures when comparing bank level data. The results also showed that distance to default has a higher level of contagion than distance to inefficacy and distance to capital. Additionally, the contagion results were steady across the banks for the different distance to risk measures, validating the outcomes from previous chapters.

Chapter 7. Contagion Risk, Regulation and Risk Management

7.1. Introduction

This chapter discusses the findings of previous chapters in a global context and how those findings can be used to manage systemic risk using regulatory control. The chapter uses qualitative deductions to look into the relationship between regulation and spillover of systemic risk, and proposes an extension of the current global risk management framework to enhance and secure better financial outcome for all the relevant stakeholders.

As discussed throughout the thesis, the importance and influence of systemic risk in the modern financial sector was put beyond doubt by the global financial crisis of 2008–2009 (Dungey, Matei, Luciani, & Veredas, 2017; Laseen, Pescatori, & Turunen, 2017). Previous authors have attributed the GFC to two major mistakes – lack of policy (Yellen, 2013) and lack of risk management control (McAleer, Jiménez-Martín, & Pérez-Amaral, 2013a, 2013b). In the aftermath of this crisis, the global financial community is taking more action to prevent any future financial catastrophe. It has accepted that prevention is a better approach than containment. In the three study chapters (4, 5 and 6), this thesis has established how contagious the current global financial system is at a both international and local settings, using the thesis's framework of distance to default, distance to inefficiency and distance to capital spillover. The results highlight the risk of another global risk spillover, given the amount of interconnectedness detected in the global banks. Thus, the objective of this chapter is to propose a rigorous risk management framework to prevent any future spillover in the global and local financial sector. In this regard, the chapter has been divided into three sub-sections: a discussion on contemporary financial regulatory issues, a proposed macro regulatory framework and a proposed inter-organisational regulatory framework.

7.2. A discussion on contemporary financial regulatory issues

The history of financial regulation is as old as financial transaction (Pagano & Volpin, 2001) and has grown incrementally over time to enhance regulatory control. Previous authors have cited three main purposes of regulation (Goodhart, 2008):

1. to constrain the use of monopoly power and the prevention of serious distortions to competition and the maintenance of market integrity;

2. to protect the essential needs of ordinary people in cases where information is hard or costly to obtain and mistakes could devastate welfare, and

3. where there are sufficient externalities that the social, and overall, costs of market failure exceed both the private costs of failure and the extra costs of regulation.

The problem with his reasoning is that while 1 and 2 suggest an interconnected and interdependent system based on pure competition, 3 points out the downfall of this model using contagion risk in the global financial system. A good example of this is the failure of Lehman Brothers, which led to catastrophic changes in the US banking sector. It begs the question, how correct is the current regulatory framework? Past authors have clearly suggested that the current model of financial regulation is too narrowly confined to firm-specific liquidity-based risk control mechanisms (Borio, 2011), when it should focus more on controlling the systemic risk spillover on a larger scale (Betz, Hautsch, Peltonen, & Schienle, 2016) using macro-prudential regulation (Jeanne & Korinek, 2013). In this regard, using the literature review and the contagion risk findings from the previous three chapters, the research proposes the following risk framework at both macro and micro levels.

7.3. A proposed macro regulatory framework

The global financial crisis has pushed most countries around the world to analyse their macro prudential strategy given the cross-border operations of the banks (J. Berrospide et al., 2016). Previous authors have noted that most countries now have difficulties regulating the banking sector because most banks operate in global domain that is outside the local legal jurisdiction (J. Berrospide et al., 2016). Thus, the effects of a change of policy or regulation in one jurisdiction spill over to others (Schimmelfennig, 2016). Keeping this in mind, the study proposes that the dominant global and local banks be divided into four types, following the precedent of the Financial Stability Board (FSB) requirement (Cohen & Scatigna, 2016). In order to convert the research outcome to practical output, the study is proposing to value a bank's spillover capacity by using distance to inefficiency and distance to capital methods only. The distance to default method is excluded in this regard as distance to capital already incorporates distance to default using Basel-prescribed capital adequacy requirements. Given the definition of efficiency, the efficiency index will represent the bank's short-term financial health and the capital index will represent the bank's long-term financial health. The study has used this methodology in the chapter on US bank-to-bank contagion (Chapter 6). In order to construct the index, one needs to find out a bank's weighted numeric position. Thus, the study has assigned (arbitrarily) an 80% value when a bank moves its shock to other banks and a 20% value when it is infected by a shock spillover. For instance, if a bank spills over to five banks and received shocks from two banks, its score will be (4 x 5) + (2 x 1), or 22.The study then put the banks into a categorical order based on their precise impact factor. In this regard, the study has distributed the banks into five categories (Tire 1 to Tire 5). Tire 1 is most active, and thus requires the highest level of supervisory regulation, while Tire 5 has the lowest spilling capacity and thus can be subjected to moderate supervisory control. The following tables (7.3.1 and 7.3.2) describe the output of the findings.

Looking Table 7.3.1, which shows a categorical list of banks with short-term contagion capacity, it is visible that there a clear pattern indicating the superiority of smaller banks. Their larger counterparts, including some GSIB banks (JP Morgan, Wells Fargo and Bank of America), show a very different pattern, falling into the second-last category (Type 3) in the list. Thus, Table 7.3.1 clearly shows the amount of inconsistency between the smallest and largest contagion capacity (16 to 152, with a mean of 46). Figure 7.3.1 also illustrates the mean-centred tendency of the contagion values with a few outliers. This can be very helpful if regulators can create the figure for other countries and compare them among themselves. This issue clearly calls for higher regulatory control of the banks placed higher in the Table.

Table 7.3.1 – Chronological list of banks with short-term contagion capacity

No	Bank	Contagion Value	Tier
1	Prosperity Bancshares, Inc	152	Tier 1
2	Freddie Mac	108	
3	Flagstar Bancorp Inc	105	
4	Synovus Financial Corp	98	
5	Ameris Bancorp	85	
6	United Bankshares, Inc.	72	Tier 2
7	Provident Financial Services, Inc.	68	
8	WesBanco, Inc	67	
9	Citigroup	66	
10	Enterprise Financial Services Corp	66	
11	Independent Bank Corporation	66	
12	United Community Banks, Inc	65	
13	First Midwest Bancorp, Inc	63	
14	Yadkin Financial Corporation	56	
15	State Street Corporation	55	
16	Goldman Sachs	54	
17	BB&T Corporation	53	
18	Cathay General Bancorp Inc	52	
19	First Busey Corporation	51	
20	Cullen/Frost Bankers, Inc	49	
21	Bancorpsouth, Inc.	47	
22	Hancock Holding Company	47	
23	Valley National Bancorp	47	
24	Premier Financial Bancorp	47	
25	Trustmark Corporation	46	
26	FNB Corporation	46	
27	Boston Private Financial Holdings Inc	45	
28	First Merchants Corporation	44	
29	Union Bankshares Corporation	44	
30	MB Financial Inc	43	
31	Capital One Financial Corporation	43	
32	Fulton Financial Corporation	42	
33	Bank of New York Mellon	41	
34	Lakeland Financial Corporation, Indiana	40	Tier 3
35	SVB Financial Group	39	
36	Texas Capital Bancshares, Inc	38	

37	Berkshire Hills Bancorp Inc	37	
38	Fifth Third Bancorp	37	
39	SunTrust Banks, Inc.	36	
40	First Citizens BancShares	36	
41	Old National Bancorp	35	
42	Chemical Financial Corporation	35	
43	First Defiance Financial Corp	35	
44	Wintrust Financial Corporation	34	
45	Brookline Bancorp Inc	34	
46	Renasant Corporation	31	
47	Charles Schwab Corporation	30	
48	1st Source Corporation	30	
49	Lakeland Bancorp, Inc	30	
50	JPMorgan Chase	28	
51	Huntington Bancshares Inc	28	
52	Wells Fargo & Company	27	
53	KeyCorp	25	
54	Bank of America Corporation	24	
55	PNC Financial Services Group Inc	24	
56	City Holding Company	24	
57	Comerica Incorporated	23	
58	ConnectOne Bancorp Inc	20	
59	Northwest Bancshares Inc	20	
60	Towne Bank	16	Tier 4

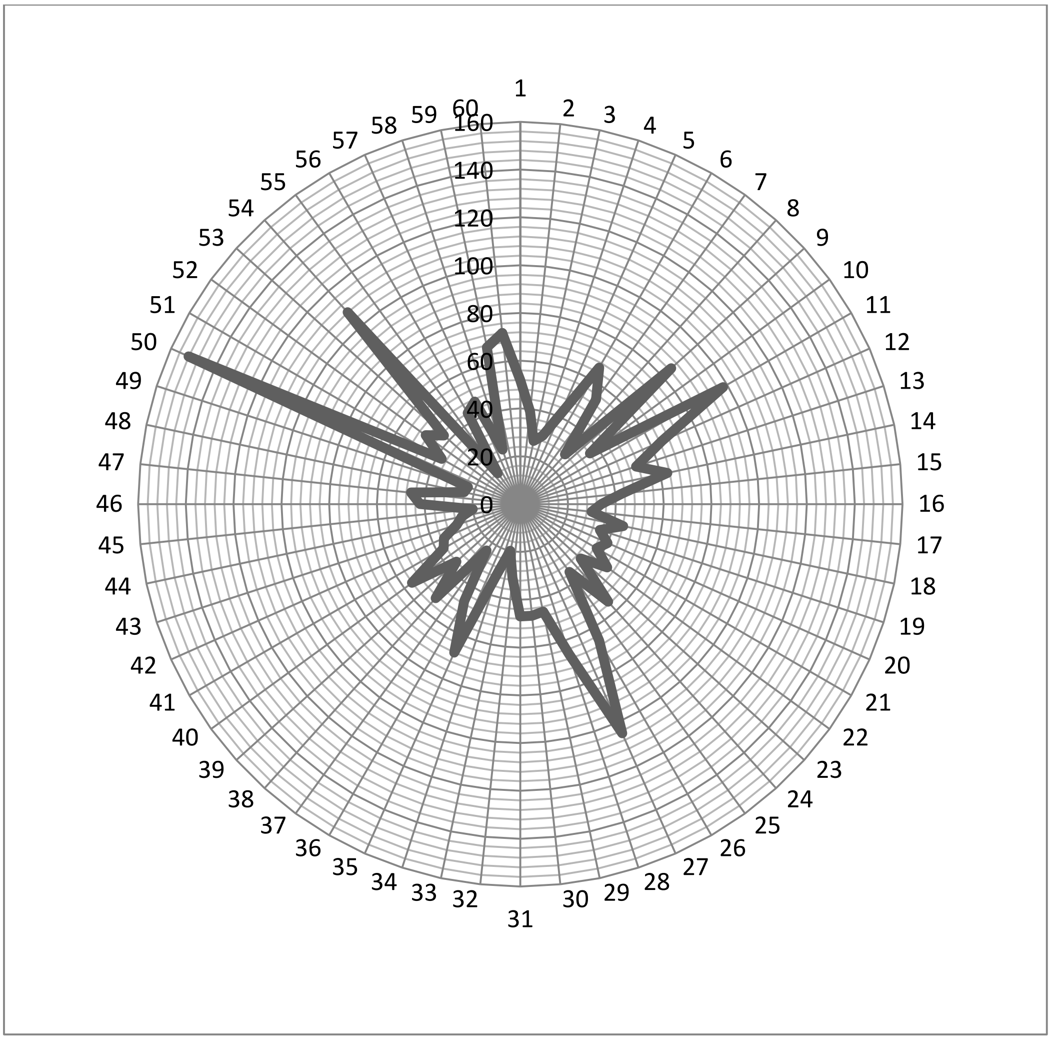


Figure 7.3.1. Spread of short-term contagion capacity

Table 7.3.2 shows a categorical list of banks with long-term contagion capacity based on distance to capital. Following the pattern of the previous table, smaller banks still have a higher impact when it comes to transmitting and receiving shocks. Figure 7.3.2 illustrates the contagion value distribution of the banks. It clearly shows that, with the exception of some outliers, most banks stay very close to the mean with a marginal increase of the spread compared to the last measure. Again, the GSIBs are all placed in the middle two tiers. Putting the contagion value distributions figures together (Figure 7.3.3) provides a complete picture of overall contagion distribution with moderate mean central tendency. It also shows that, excluding outliers, both contagion distributions show similar spillover capacity.

Table 7.3.2 – Chronological list of banks with long-term contagion capacity

No	Bank	Contagion Value	Tier
1	Hancock Holding Company	153	Tier 4
2	SunTrust Banks, Inc.	104	
3	Premier Financial Bancorp	99	
4	First Midwest Bancorp, Inc	92	
5	Comerica Incorporated	87	
6	Fulton Financial Corporation	85	
7	State Street Corporation	72	Tier 3
8	MB Financial Inc	71	
9	Yadkin Financial Corporation	71	
10	Wintrust Financial Corporation	68	
11	FNB Corporation	67	
12	United Bankshares, Inc.	65	
13	Lakeland Financial Corporation, Indiana	64	
14	City Holding Company	62	
15	Brookline Bancorp Inc	60	
16	Trustmark Corporation	60	
17	Texas Capital Bancshares, Inc	59	
18	Capital One Financial Corporation	55	
19	Goldman Sachs	54	
20	First Merchants Corporation	50	
21	Bank of New York Mellon	49	
22	Flagstar Bancorp Inc	49	
23	First Busey Corporation	48	
24	Boston Private Financial Holdings Inc	48	
25	Charles Schwab Corporation	47	
26	United Community Banks, Inc	47	
27	SVB Financial Group	44	
28	KeyCorp	43	
29	WesBanco, Inc	43	
30	JPMorgan Chase	39	Tier 2
31	Synovus Financial Corp	39	
32	ConnectOne Bancorp Inc	39	

33	Lakeland Bancorp, Inc	39	
34	Freddie Mac	38	
35	Independent Bank Corporation	36	
36	Cullen/Frost Bankers, Inc	35	
37	Prosperity Bancshares, Inc	33	
38	Cathay General Bancorp Inc	32	
39	First Citizens BancShares	32	
40	1st Source Corporation	31	
41	Chemical Financial Corporation	30	
42	Bank of America Corporation	30	
43	Wells Fargo & Company	29	
44	Ameris Bancorp	29	
45	Renasant Corporation	28	
46	Old National Bancorp	27	
47	Berkshire Hills Bancorp Inc	27	
48	First Defiance Financial Corp	26	
49	PNC Financial Services Group Inc	26	
50	Bancorpsouth, Inc.	24	
51	Valley National Bancorp	24	
52	Huntington Bancshares Inc	24	
53	Northwest Bancshares Inc	23	
54	Union Bankshares Corporation	23	
55	Citigroup	22	
56	BB&T Corporation	22	
57	Enterprise Financial Services Corp	19	
58	Towne Bank	18	
59	Fifth Third Bancorp	17	
60	Provident Financial Services, Inc.	2	Tier 1

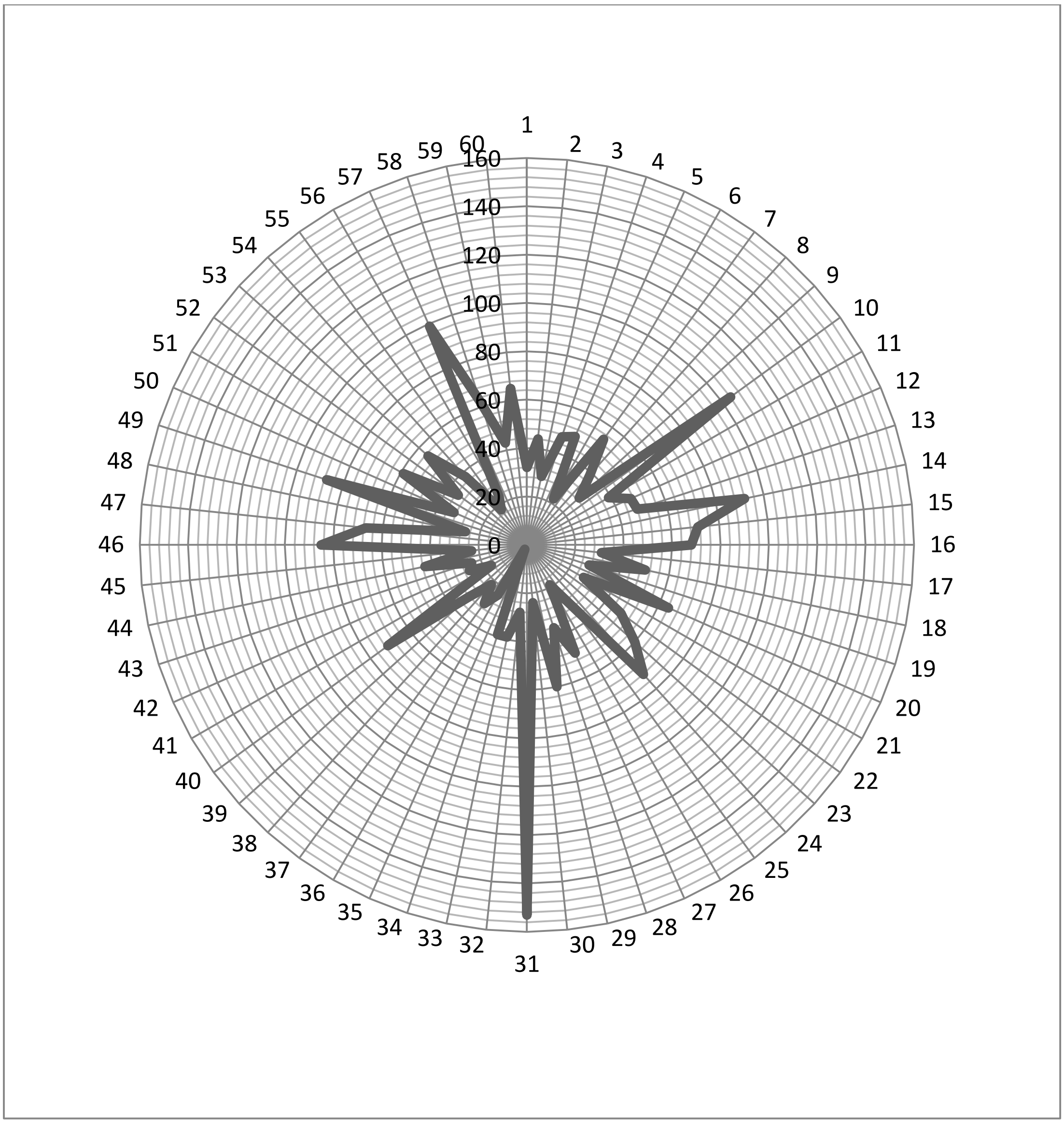


Figure 7.3.2. Spread of long-term contagion capacity

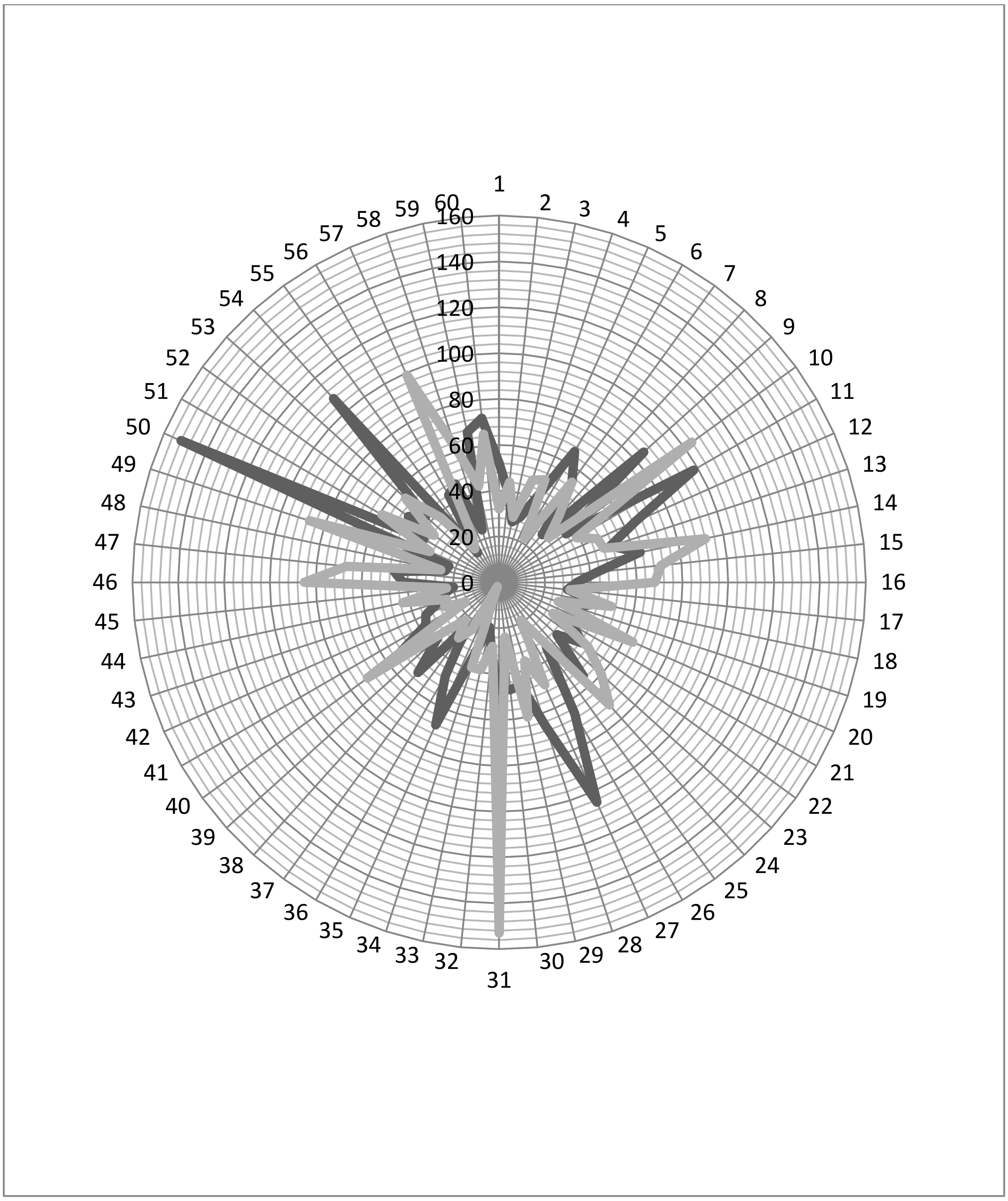


Figure 7.3.3. Spread of short-term and long-term contagion capacity

The study suggests that any bank in the first category (Type 1) of the short-term or long-term contagion capacity table should be subject to a high degree of regulatory control to enforce not only better capital governance or liquidity requirements, but also overall financial governance, as they have a huge impact on other financial institutions. For the banks in the second and third categories, the regulators may adopt more graduated governance control in line with the current practice, while Type 4 institutions can continue to conduct business under current regulations, as they pose no real threat to their peers.

7.3. A proposed micro regulatory framework

A financial institution's contagion risk management is not only dependent on how shocks spread or spill over to other institutions but also on how much of the risk it can mitigate using internal control mechanism. Keeping this in mind, the findings from the literature review are used to create a modern framework for internal risk management for individual financial institutions (Figure 7.3.1). This divides risk management into two sub-components, internal and external. External pressure factors influence the institution's risk management practice from outside the institution. They create boundaries and guidelines for the participating institutions to work within. Previous authors have identified such factors when considering risk management frameworks, including the regulatory environment, stakeholders' influence, legal framework, industry standard and social norms. The regulatory environment generally refers to the implementation of Basel standards in the banking world (Young, 2013). Most countries have accepted Basel standards for their internal financial practices. This regulatory pressure plays an enormous role in determining the risk management practice standards in any country. Stakeholders are defined as the pressure groups outside the bank's legal structure and can be seen as an interested party with regard to the risk management practices of the institution given the interconnected nature of the post-GFC financial world (Hopt, 2013). Legal framework refers to the laws governing the banks in the designated countries

(Neyapti & Dincer, 2014). Industry standards for risk prevention are important given that most banks' first point of reference for risk management procedures is what other peers are doing in risk mitigation and control. Past researchers have clearly suggested that all banks try to maintain same standard of risk prevention in banking industry, as required by the Basel Accords (Powers, Hassan Al-Tamimi, & Mohammed Al-Mazrooei, 2007). The last of the external pressures is social norms, which have been proven to have significant influencing power on the risk management conduct of the banks (Gathergood, 2012).

On the other hand, the internal risk management practice of the banks includes four process steps – identification, analysis, treatment and review. The process starts by identifying where the risk is. This may be trigged by an underlying situation recognised with the help of internal or external auditing (Gaganis, Pasiouras, & Spathis, 2013). Then the risk can be analysed through industry comparison-based impact studies (Kanagaretnam, Lim, & Lobo, 2013). Bankers may use sample implementation of different risk management techniques before widespread implementation of these measures. If the sample implementation is successful, then these techniques can be used throughout the financial institutions. In the final stage, it is highly recommended that banks periodically review their risk management standards to ensure a complete risk prevention guarantee.

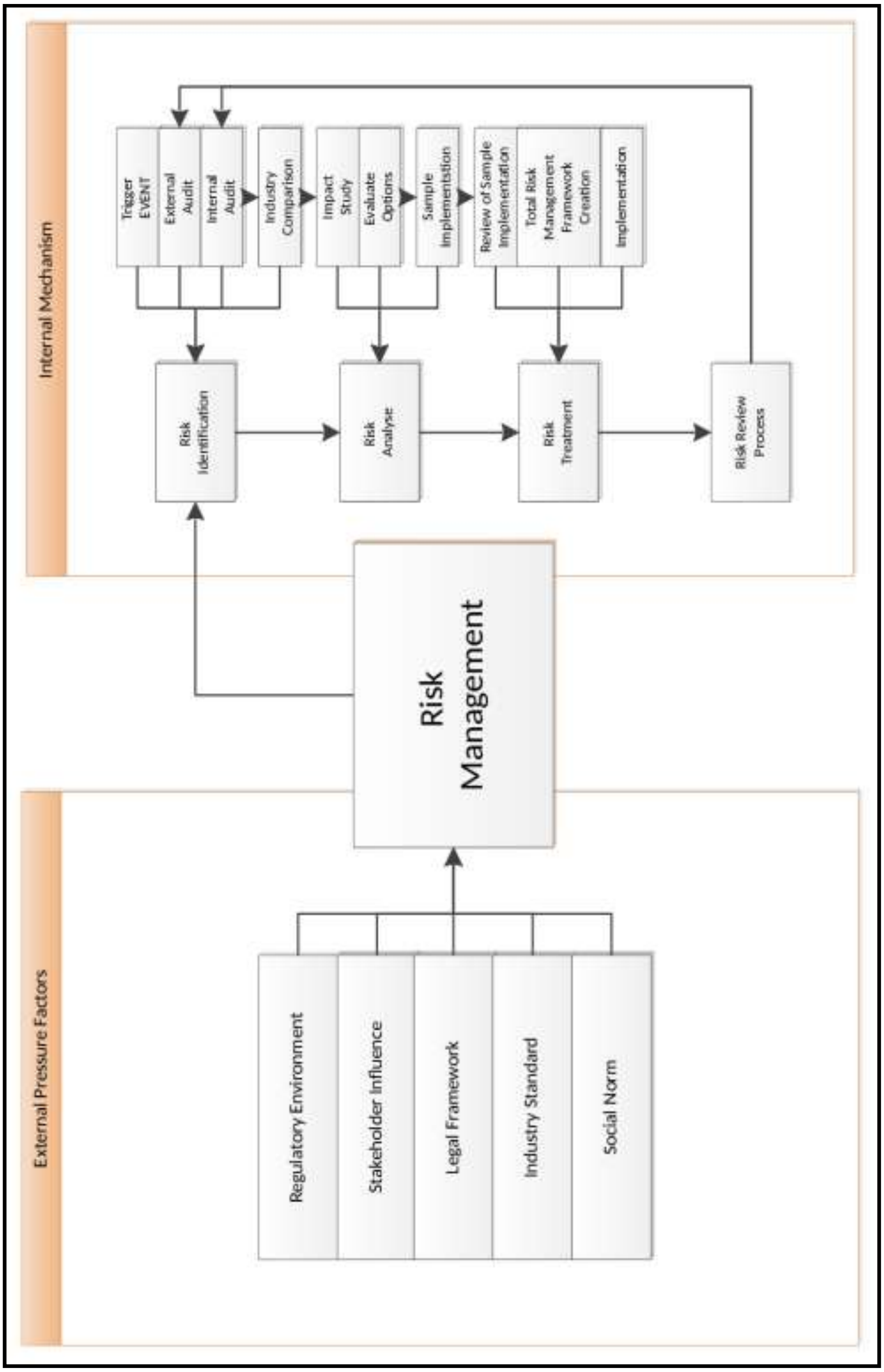


Figure 7.3.1. Author's framework for internal and external risk management

7.4. Conclusion

This chapter examined the findings of the previous three chapters and integrated their findings to create a modern day risk management and risk regulation framework at both micro and macro level. Banks were categorised into four types based on their potential spillover impact in short and long term. It was suggested that banks in the first category should be subject to a high degree of regulatory control to enforce not only better capital governance or liquidity requirements but also overall financial governance, as they have a potentially huge impact on other financial institutions. For the banks in the second and third categories, a more graduated governance mechanism may be adopted in line with current practice, while the fourth category can continue doing business under current regulation, as they pose no significant threat to their peers. Finally, a new generic internal risk management framework for financial institutions was suggested.

Chapter 8. Conclusion

8.1. Introduction

This chapter summarises the thesis and its contribution to the knowledge of financial contagion in the global and local banking industry and its policy implications. The limitations and opportunities of this study are also discussed to suggest avenues for future study.

8.2. Summary of author's contributions from the chapters

Financial contagion revolves around two schools of thought, financial soundness and financial distress. This thesis has shown how value shock in one bank or economy moves into other banks or economies, creating contagion risk. However, the real value of this thesis is not in showing that value shocks move, but rather in showing *how* they move – where they move from, and to whom they move, which is the essential component of an effective risk management agenda. At the same time, this thesis also applies theoretical knowledge to systemic risk-based model generation and operational practical guidelines for supervisory authorities. The paragraphs below provide short summaries of the significant focuses of the preceding chapters.

In Chapter 1, the context and background of the thesis were discussed to define the objective of this research, which includes an outline for possible innovation and upgrading of global and local contagion risk management. Past authors have clearly suggested that contagion risk is a crucial issue in the modern financial world (Elliott et al., 2014; Tonzer, 2015). Nevertheless, not enough research has been done on global and local contagion risk analysis using different distance to risk measures. The chapter outlined the methodology used in the thesis and defined the ethical and technical issues associated with the research.

The second chapter has started with the definition of risk then moved onto risk management through the Basel framework, finishing with a review of the existing literature on contagion risk. This chapter provided a basic understanding of risk and risk management terminologies and what past authors have said about them in their research. It described the very core of risk and risk management as finding uncertainties and minimising the damage from them. Contagion risk was defined as an extreme macro level phenomenon arising from spillover between different entities. The chapter deduced that, by understanding the nature of contagiousness within the global and local banking industry, it is possible to minimise the value degradation arising from these sorts of risks. Thus, the objective of this thesis should be to look into the contagious nature of the global and local banking industries and identify the movement of shocks to understand the risk arising from such spillover. The beauty of this process is that, once the movement of contagious risk is understood, the stakeholders can design controls to minimise its impact, thus creating an effective risk management framework.

Chapter 3 detailed the methodology used in this thesis. It described the specific distance risk-based multinomial regression model used in this to address the research questions. In order to ensure the highest quality of research outcomes, four different aspects of the project were acknowledged: factor validity, internal validity, external validity and reliability. These were converted into the research protocols followed throughout the thesis.

Chapter 4 investigated the contagion risk for the global banking environment using three different distance to risk measures from the methodology. Extreme shocks for the top global top banks were modelled as a function of extreme shocks experienced by other banks in country-level settings. Four separate conditions of financial states were created in this regard. The probability of these states moving through one country's economy to another was calculated using a multinomial logistic model. Overall, the findings using all three different distance to risk measures showed a strong correlation between the sample countries' banking systems, particularly between the UK and the US. Other countries' banking systems had an moderate effect on each other. These results also indicated that less developed or developing economies' banking systems are more resistant to from financial shock contagion than their counterparts did. The key challenge for the future is to ensure adequate collaboration and cross-border supervision at the global level.

Chapter 5 explored the contagion risk for the US banking sector based on fifteen states using three diverse distance to risk procedures. Extreme shocks for US states were modelled as a function of extreme shocks faced by other US states or foreign countries. Four distinct settings of financial stress were used in this regard. The likelihood of these stress conditions moving through the sample was calculated using a multinomial logistic model. Generally, the findings from all three distance to risk procedures indicated robust correlation between the US states and between US states and other countries. The results also indicated that larger states are more resistant to financial shock transfer.

Chapter 6 explored the contagion risk for the US banking sector based on sixty of the largest US banks using three distance to risk procedures. Extreme shocks for US banks were modelled as a function of extreme shocks confronted by other banks in the sample. The probability of these stress conditions moving through the sample was calculated using multinomial logistic regression analysis. In general, the findings from all three distance to risk measures identified strong association between the US banks in the sample. The outcomes also indicated that minor banks both transmit and receive more value shocks than their larger counterparts, and that larger banks exhibit higher resistance to shock than their smaller colleagues in all three distance to risk measures. There was no evidence of superiority of GSIB banks. The most important observation was the minimal amount of state bias within the sample. It was also found that distance to default has the highest amount of contagion (compared to distance to inefficacy and distance to capital).

Chapter 8 examined the findings of the previous three chapters and integrated the findings to create a modern day risk management and risk regulation framework at both micro and macro levels. The banks were divided them into 4 types based on their spillover impact in the short and long term. Under the proposed framework, banks in the highest category of short-term or long-term contagion capacity should be subject to a high degree of regulatory control to enforce not only better capital governance and liquidity requirements but to also overall financial governance, as they have a huge potential impact on the other financial institutions. For the banks in the second and third categories may be subject to more graduated governance control in line with current practice, while for Type 4 banks current regulation is sufficient as they pose no real threat to their peers. A new generic internal risk management framework for financial institutions is also suggested.

8.3. Conclusion

Earlier in this chapter, the subsections summarised the academic and applied input of this thesis based on the research undertaken. In concluding, it can be stated that contagion risk analysis using different distance to risk measures (DD, DI and DC) is still at a foundational level. The literature review chapter identifies the scarcity of high value research in this field. However, many modern scholars are disinclined to look into this subject given their deep attachment to traditional risk measurement tools. Table 7.1 summarises and ends the thesis, outlining the significant outcomes of the research together with the limitations and suggestions for future research.

Table 7.1 The end view

Topic	**Summary**
Title	A study of contagion in global and local banking industry
Context	Global and Local (US) banking industries
Methodology	Quantitative – Multinomial logistic Regression
Key findings	• Strong correlation between sample countries' banking systems especially those of the UK and US. Other countries' banking systems have a moderate effect on each other when it comes to shock transfer. • Less developed or developing economies' banking systems are more immune to financial shock. • Strong correlation between sample US states and banks in the sample. • Larger US states are more immune to financial shock.
Limitations	• Big data project. The printed calculation results from this thesis are more than 2500 pages. • The thesis has only used local currency given the

	data availability but other authors has suggested to use both local and USD currency when calculating return (Mink, 2015).
Future research agendas	• To compare different models of risk calculation as input variables and compare them with the thesis’sthesis results. • To identify the impact of technological advancement in contagion risk analysis. • To identify the differences between the three different distance to risk measures global level.

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