NETWORK MODEL AND MACROECONOMICS OF SYSTEMIC RISK

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2022

Dedication

To my loving wife, Dina.

The spirit of my life, Galuh, Puteri and Bintang

My inspiration, the Parents, Brothers and Sisters of the Salim family.

Acknowledgements

I would like to express my respect and gratitude to Prof. Kevin Daly and Assoc. Prof. Qiongbing (Linda) Wu for their relentless effort, time and assistance guiding me during this challenging journey. In the face of the COVID-19 pandemic, you showcased your amazing flexibility and dedication to ensuring I completed my studies.

This PhD study received support and funding from:

- the Australian Government through the Australia Awards Scholarship (OASIS ID ST000SS21)
- Otoritas Jasa Keuangan (ND 7/MS.21/2018 dated 5 January 2018)

Thank you for the trust and opportunity.

I would also like to thank the discussants and participants of the 15th BMEB International Conference and the International Conference of Banking and Finance 2021 for their valuable comments and inputs.

Capstone Editing and Magnum Proofreading provided copyediting and proofreading services for Chapters 1–8, the reference list and appendices, according to the guidelines laid out in the university-endorsed national 'Guidelines for Editing Research Theses'.

Statement of Authentication

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text. I hereby declare that I have not submitted this material, either in full or in part, for a degree at this or any other institutions.

[redacted]

Sydney, 4 March 2022

Journals/Proceeding/Presentations

Part of this thesis have been published in peer-review journals, conference proceedings and presented in the international conferences.

Peer-reviewed journal articles:

1. *Journal of Risk and Financial Management*, indexed in Web of Science, ABDC, DOAJ, RePEc, EconLit.
   Salim, MZ & Daly, K 2021, 'Modelling systemically important banks vis-à-vis the Basel Prudential Guidelines', *Journal of Risk and Financial Management*, vol. 14, no. 7, DOI 10.3390/jrfm14070295.
2. *Risks*, indexed in Scopus(Q2), Web of Science, ABDC, DOAJ, RePEc, EconLit.
   Mohamad Rizan, Muhammad Zulkifli Salim, Saparuddin Mukhtar, and Kevin Daly, 2022, 'Macroeconomics of Systemic Risk: Transmission Channels and Technical Integration', *Risks 10: 174, https://doi.org/10.3390/risks10090174.*
3. *Heliyon*, indexed in Scopus(Q1), Web of Science, PubMed.
   M. Zulkifli Salim, Dadang Ramdhan, and Kevin Daly, 'Returns Co-movement and Interconnectedness of Financial System', (accepted for publication).
4. *Cogent Economics and Finance*, indexed in Scopus(Q2), ABDC, Web of Science.
   Zuhrotun, M. Zulkifli Salim, and Kevin Daly, 'Returns Co-movement and Interconnectedness: Evidence from Indonesia Banking System', (accepted for publication).

Conference proceeding:

1. Salim, MZ et al. 2021, 'Modelling Indonesia's systemically important banks vis-à-vis the Basel Prudential Guidelines', International Conference of Banking and Finance 2021, June 2021, Ho Chi Minh City, Vietnam (sciencesconf.org:icbf2021:352542).

International conferences:

1. 15th Bulletin of Monetary Economics and Banking, 2 September 2021, Bank Indonesia – Asia Pacific Applied Economic Association, Jakarta, Indonesia.
2. International Conference of Banking and Finance 2021, 28 September 2021, University of Leicester, University of Economics Ho Chi Minh City, Chung-Ang University, Binh Duong University, Thu Dao Mot University, CFVG and Institute of Business Research, Ho Chi Minh City, Vietnam.

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List of Abbreviations

ARCH	Autoregressive Conditional Heteroskedasticity
BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlement
CB	Commercial Banks
CDS	Credit Default Swap
CISS	Composite Indicator of Systemic Stress
CoVaR	Conditional Value at Risk
DCC	Dynamic Conditional Correlation
D-SIBs	Domestic Systemically Important Banks
ECB	European Central Bank
ES	Expected Shortfall
EVT	Extreme Value Theory
FMM	Finite Mixture Model
FSB	Financial Stability Board
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GLE	Generalised Least Square
G-SIBs	Global Systemically Important Banks
GSE	Government Support Entities
IC	Insurance Companies
IMF	International Monetary Fund
IB	Investment Banks
JSX	Jakarta Stock Exchange
LRMES	Long-Run Marginal Expected Shortfall
MES	Marginal Expected Shortfall
OJK	Otoritas Jasa Keuangan (Indonesia Financial Services Authority)
OLS	Ordinary Least Square
OTC	Over the Counter
PCA	Principal Component Analysis
POJK	Peraturan Otoritas Jasa Keuangan (Indonesia Financial Services Authority Regulation)
RWA	Risk Weighted Assets

SES	Systemic Expected Shortfall
SIBs	Systemically Important Banks
SIFIs	Systemically Important Financial Institutions
SRISK	Systemic Risk Measure
UK	United Kingdom
US	United States
VaR	Value at Risk

Abstract

This thesis highlights the importance of a holistic approach to understanding systemic risk. The cost of crises and their effects on the economy are catastrophic, thus necessitating a clearer understanding and proper risk mitigation to lessen future financial crises. In considering economic crises, the Basel guidelines emphasise the size of institutions and have limited reflection on how crises might disperse across the financial system network. This thesis aims to empirically comprehend the connection between the tools used by academics in field and systemic risk studies and the practical guides endorsed by policymakers. This study also explores the risk escalation and direction from or to other financial institutions by employing the network model. Another objective is to propose robust integration of micro and macro data to develop systemic risk monitoring tools for practical use. The missing link in current systemic risk research could be used to assess overall risk endogenously and externally expose systemically important financial institutions

Assessment of systemically important banks (SIBs) employed three theoretical models—conditional value at risk (CoVaR), marginal expected shortfall (MES) and systemic risk measure (SRISK)—and compared the results with the current Basel indicator-based results. Using Indonesia commercial bank datasets for the 2008–2019 period, the findings show that all three theoretical approaches have positive association with the Basel-based results, though the 'best' results vary across models. SRISK delivers more consistent rankings over the sample period, but for inter-theoretical approaches, CoVaR – MES has the highest positive correlation that converted to certain degree of rankings similarity. This finding suggests that scholars can build on or extend the estimation model to include bank balance sheets and economic data to better capture the specific risks of SIBs.

This research also explores how capital market data and asset returns can be a good proxy to detect interconnectedness and map risk in the financial system. The sample employs a mixture of Indonesian banks' stock market and prudential data for the 2012–2019 period. Using principal component analysis and Granger network centrality, the core banks in the network could explain variance, risk commonality and shocks propagation. The outcomes were tested in line with Basel-based calculations to score interconnectedness. The dominance of large banks in the centrality measures also raises the issue of substitutability. This study extends existing theories to provide a basis for policymakers to develop supervision frameworks to impede systemic risk.

To further investigate the possibility of using asset returns to mitigate financial contagion, Chapter 6 employs a US dataset for the 2002–2019 period. Pairwise returns

correlation indicate the interconnectedness at the preliminary stage. The results using US data confirm the results using Indonesian data—principal component analysis captured a significant portion of variance and detected the co-movement and highly connected state of financial markets during economic crises. Granger centrality tested with pairwise directional variance decomposition indicates the importance of banks and insurance companies in the US financial system. Using multiple, complementary network models to validate and calibrate the systemic institutions list is recommended for policymakers.

A balanced assessment of systemic financial institutions requires the integration of macro and micro granular datasets. This requires investigating how macroeconomic shocks affect systemic risk through several transmission channels. Employing Indonesian datasets for the 2008–2019 period, we expand on the three market models (CoVaR, MES and SRISK) using linear, ARCH and GARCH regression. The findings conclude that stock beta, market index and exchange rate volatility amplify the systemic risk, while the liquidity spread outcome varies depending on different model variables and the deepness of a country's financial market. This thesis recommends practical integration of risk into the systemic risk assessment framework and its technical calculation to capture the holistic exposure of systemically important financial institutions.

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Chapter 1: Introduction

1.1 Introduction

Banking crises are known triggers for further financial instability and economic downturns across countries. The Basel Committee on Banking Supervision (BCBS) revealed that, on average, banking crises occur once every 20–25 years, with the exception of the period after the end of the Second World War until the early 1970s/1980s (BCBS 2010). Reinhart and Rogoff (2013) found 34 crises occurred in the last 25 years among BCBS member countries. Laeven and Valencia (2013) similarly found 24 banking crises among BCBS member countries from 1985–2009. Differences in the number of identified banking crises are due to different classifications and assumptions by researchers. Table 1.1 lists the dates and countries of identified banking crises among BCBS member countries.

Table 1.1. Banking Crises in BCBS Countries

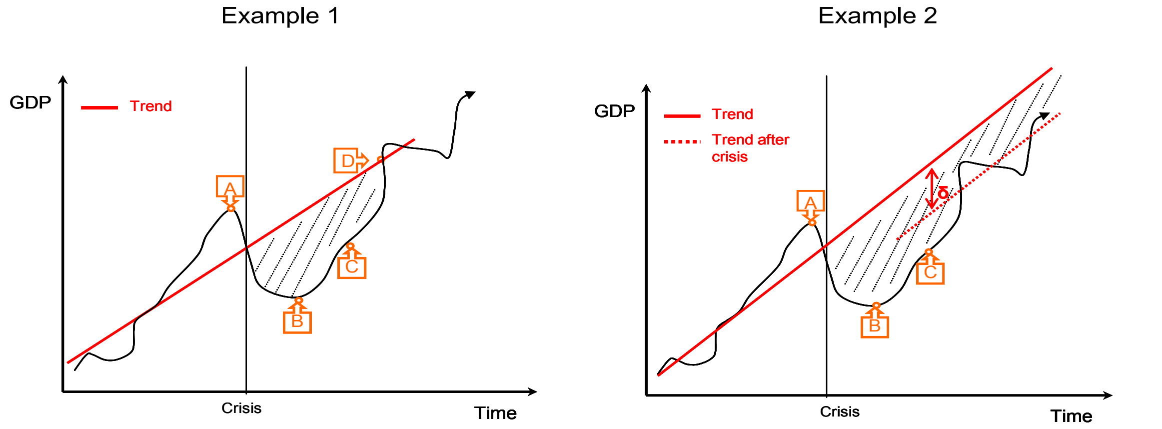
Country	Reinhart and Rogoff (2008)	Laeven and Valencia (2008)
Argentina	1989, 1994, 2001	1989, 1995, 2001
Australia	1989	–
Belgium	2008	2008
Brazil	1990, 1994	1990, 1994
Canada	–	–
China	1997	1998
France	1994, 2008	2008
Germany	2007	2007
Hongkong	1998	
India	1993	1993
Indonesia	1992, 1997	1997
Italy	1990	–
Japan	1992, 2008	1997, 2008
Korea	1986, 1997	1997
Luxemburg	2008	2008
Mexico	1992	1994
Netherlands	2008	2008
Russia	1995, 1998	1998
Saudi Arabia	–	–
South Africa	1989	–
Sweden	1991	1991
Switzerland	2008	2008
Turkey	1991, 2000	2000
United Kingdom	1991, 1995, 2007	2007
United States	2007	1988, 2007

Source: BCBS (2010).

The economic costs of the most recent 2008 banking crises were catastrophic, and their wider effects and the associated government bailouts prompted significant social criticism and discontent. The United States (US) Government Accountability Office (2013) identified the 2008 financial crisis as the most severe since the Great Depression of the 1930s. Data on US banking crises indicates that after such crises, on average, US GDP output falls by over 9% (from peak to trough), with an associated recession lasting for about two years. The same report found that from 2007–2009, US gross domestic product (GDP) fell from US$13.3 trillion to US$12.7 trillion (nearly 5%) and real GDP did not reach pre-recession levels until the third quarter of 2011. The output losses associated with the crises range from several trillion to over US$10 trillion. Research by Boyd, Kwak and Smith (2005) indicates that output losses exceeded 100% of pre-crisis GDP. The crises also affected unemployment, household wealth and number of foreclosures. For example, during the 2008 financial crises, US unemployment peaked at around 10% in October 2009 and remained at 8% for over three years.

BCBS (2010) reported the cost of the banking crises using the approach of comparing pre-crises and post-crises GDP trends (see Figure 1.1). The cumulative losses could be bigger if estimated in the long run, as shown in Figure 1.1.

Figure 1.1. Measuring the Cost of Crises: A Schematic Overview



Point A: pre-crisis peak. Point B: post-crisis trough. Point C: GDP growth equals trend GDP growth for the first time after the crisis. Point D: the level of GDP returns to the pre-crisis level.

Source: BCBS (2010).

Researchers have used a variety of methods and assumptions to measure the effects of the banking crises and all have reached the same conclusion: the magnitude of losses was enormous. On average, output losses across all studies are 63% of pre-crises output, as shown in Table 1.2. All of the above demonstrates the need for regulatory policymakers to be able to supervise and mitigate banking crises by preventing their occurrence or at least restricting financial contagion and systemic risk to other financial institutions.

Table 1.2. Cost of Banking Crises Relative to Pre-Crises GDP

Study	Cumulative losses	Result reported in the literature				
		Mean	*Min*	*Max*	*Industrial economies*	*Emerging economies*
Difference between GDP at the beginning and end of period						
Period from peak to trough						
Reinhart and Rogoff (2009)		9	0	29		
Cecchetti et al. (2009)		9	0	42		
Period until growth rate recovers						
Bordo et al. (2001) (sample 1973–1997)		6			7	6
Bordo et al. (2001) (sample 1919–1939)		11			12	9
IMF (1998)		12			10	12
Hoggarth et al. (2002)		14			13	15
Demirguc-Kunt et al. (2005)		7				
Hutchison and Neuberger (2005)		10				
Infinite horizon (permanent effects)						
Cerra and Saxena (2008)	158	7.5			15	4
Turini et al. (2010)	197	9.4				
IMF (2009)	210	10			11	5
Furceri and Zdzienicka (2010)	95	4.5				
Furceri and Mourougane (2009)	42	2	1.5	4		
Barrel et al. (2010a)	42	2	0	23		
Cumulative losses						
Period from peak to end of crises						
Hoggarth et al. (2002)	16	16	0	122	21	14
Laeven and Valencia (2008)	20	20	0	123		
Haugh et al. (2009)	21	21	10	40		
Cecchetti. et al (2009)	18	18	0	130		
Infinite horizon (permanent effects)						
Boyd et al. (2005) Method 1	63	63	0	194		
Boyd et al. (2005) Method 2	302	302	0	1041		
Haldane. (2010)	200	200	90	350		
Crises have no permanent effects						
Average cumulative losses	19					
Median cumulative losses	19					
Crises have permanent effects						
Average cumulative losses	145					
Median cumulative losses	158					
All studies						
Average cumulative losses	106					
Median cumulative losses	63					

Source: BCBS (2010).

Since the banking industry is the main player in most countries' financial systems, it is crucial to safeguard against systemically important banks (SIBs) failing and precipitating a banking crisis. BCBS issued methodology guidelines in 2013 and updated these with the revised assessment framework in their 2017 consultative paper to determine global systemically important banks (G-SIBs). Based on the current methodology, G-SIB score is calculated using over 12 indicators grouped into five categories of systemic importance (BCBS 2014). The score calculation is relatively simple, with the weight proportion equally divided into 12 indicators from the data compiled from micro-level or bank balance sheet data. Exploring and developing models and methodologies of how SIBs affect the whole banking system remains a popular and interesting area of research due to the relative recency of the guidelines. The first guideline issued by the Bank for International Settlement (BIS) in November 2011 (in response to the 2008 financial crises) acts as a guideline for banking regulation in many countries. The Financial Stability Board (2019) released a list of 30 G-SIBs allocated to buckets corresponding to required levels of additional capital buffers for higher loss absorbency, as shown in Table 1.3

Table 1.3. Global Systemically Important Banks as of 2019

Bucket 5 (3.5%)	**Bucket 4 (2.5%)**	**Bucket 3 (2.0%)**	**Bucket 2 (1.5%)**	**Bucket 1 (1.0%)**
Empty	1. JP Morgan Chase	2. Citigroup 3. HSBC	4. Bank of America 5. Bank of China 6. Barclays 7. BNP Paribas 8. Deutsche Bank 9. Goldman Sachs 10. Industrial and Commercial Bank of China Limited 11. Mitsubishi UFJ FG 12. Wells Fargo	13. Agricultural Bank of China 14. Bank of New York Mellon 15. China Construction Bank 16. Credit Suisse 17. Groupe BPCE 18. Groupe Crédit Agricole 19. ING Bank 20. Mizuho FG 21. Morgan Stanley 22. Royal Bank of Canada 23. Santander 24. Société Générale 25. Standard Chartered 26. State Street 27. Sumitomo Mitsui FG 28. Toronto Dominion 29. UBS 30. UniCredit

Source: FSB (2019).

For country-level assessment, BIS allows local authorities to make discretionary adjustments of the principles, with the aim to capture the country's banking characteristics and negative externalities of the local economy.

The SIB assessment is crucial and challenging to explore because the failure of a firm to meet its obligations to creditors and customers could have significant adverse consequences for the financial system and trigger systemic risk through contagion effect. The Reserve Bank of Australia (2014) defines systemic risk as the risk of financial system disruption so widespread or severe that it causes, or is likely to cause, material damage to the economy. The present research employs a broad definition of systemic risk, based on studies such as Acharya (2009);

FSB, IMF and BIS (2009); Caballero (2010); and Rosengren (2010). Our aim is to conduct robust research that incorporates a range of variables from both the global- and country-level assessment.

The issue of contagion emerges as the result of a bank's daily operational activities and transactions, where they interact with other banks or financial institutions to manage liquidity and risks through interbank placement, bank funding and liabilities, thereby constructing a complex network within the financial sector. The implications of such activities are counterparty risk and systemic risk when a bank's failure to meet its obligations affect other banks or financial institutions in the financial system. The European Central Bank (ECB) held a workshop in October 2009 to discuss recent advanced methods employed in network analysis (ECB 2009b). Different models of network analysis allow researchers to highlight market infrastructure oversight with different data and statistical methods.

Some of the main papers are Acharya et al. (2017), proposing systemic expected shortfall (SES) using the stock price and credit default swaps spread; Brownlees and Engle (2017), introducing systemic risk measure (SRISK) method to predict the ranking of financial institutions at various stages of the 2008 financial crises; and Billio et al. (2012), attempting to analyse connectedness using principal component analysis (PCA) and Granger causality. Other important contributions include Chan-Lau (2010), using balance sheet–based network analysis to evaluate interconnectedness risk in mature and emerging market countries under extreme adverse scenarios; Elsinger, Lehar and Summer (2006a), extending the model used by Eisenberg and Noe (2001) to include uncertainty to quantify the correlated exposure and domino effect using Austria bank data; and Elsinger, Lehar and Summer (2006b), using 10 United Kingdom (UK) major banks' stock market return data over a one-year period to show how to use publicly available data to analyse the network analysis correlated exposure and mutual credit relation that may cause a domino effect.

In the context of Indonesia and compliance with BCBS principles, regulators use the guidelines to determine G-SIBs by considering banks' size, interconnectedness, substitutability and complexity (BCBS 2012). BIS also advised local authorities to consider negative externalities of the country's economy. Using market shocks as a factor to determine SIBs is crucial, as demonstrated in Indonesia during the 2008 financial crises. Our research defines 'market shocks' as the dynamic of economy condition as reflected in various macroeconomic and financial sector indicators. In the midst of the 2008 financial crisis, the Indonesian central bank (Bank Indonesia) and government decided to bail out Century Bank, a medium-sized bank in terms of total assets, interbank linkages and market share in the Indonesian banking system.

Their argument for this was that closing a bank of any size during economic turbulences would trigger a bank rush and risk contagion effect.

Assessing SIBs and systemic risk complexity requires many variables, and studies are mixed on giving more weight to the network or interconnectedness between financial institutions. Roengpitya and Rungcharoenkitkul (2011), assessing systemic risk using Thailand banking system data, find that bigger banks contribute more to systemic risk, but bank size is far from being the dominant factor. Using monthly banking supervision data, they applied conditional value at risk (CoVaR), as introduced by Adrian and Brunnermeier (2016), to measure the financial linkages and revealed that institutions that are more financially linked have more effect on systemic risk in a banking system. A similar result was reported by Krause and Giansante (2012), who developed a model of interbank loans given and received by banks of different sizes. They found that the size of a failing bank has limited effect on the number of banks affected by contagion, while network structure has a much more significant effect on systemic risk. The case of Northern Rock in the UK illustrates how a medium-sized institution suffering liquidity squeeze can trigger negative network externalities (IMF 2009).

In Indonesia, despite being a G-20 member and the biggest economy in South East Asia, research on SIBs and systemic risk study is quite limited. Hermanto and Ayomi (2014) applied the Merton model (Merton 1974) to identify the probability of default for over 30 banks in Indonesia during 2002–2013. The Merton model relies on the assumption of credit risk as being reflected in a firm's debt equity or capital structure. They identified the role of financial linkages across banks by calculating CoVaR under financial distress condition. Their results showed bigger banks contributed more to financial instability during times of financial crisis. Fadhlan (2015) used Granger causality to analyse 37 banks listed on the Indonesia Stock Exchange. The banks' modelled operational activities (i.e., causal relationships) were used as a basis to calculate the degree of Granger causality to resemble systemic risk. Using panel data from 2008–2014, Fadhlan found that in-degree centrality significantly affected the vulnerability of individual banks to other banks' failure. Muharam and Erwin (2017) estimated the CoVaR of the nine biggest banks in Indonesia using quantile regression. They found that the magnitude of individual bank risk is not proportional to a bank's systemic risk contribution. Additionally, a bank's total assets are not sufficient information with which to assess a bank's contribution to the systemic-wide banking system. Similarly, Zebua (2011) used CAMEL ratios and Adrian and Brunnermeier's (2016) CoVaR concept to measure systemic risk in the Indonesian banking system. They concluded that every individual bank contributes to systemic risk to some extent, but the VaR rankings of individual banks have low correlation with systemic risk level.

De Bandt and Hartmann (2000) and Bisias et al. (2012) show that there has been little consideration or analysis in SIB and systemic risk research of the macroeconomic factors that may be behind contagious default. Further, few researchers have analysed macroeconomic indicators relation to banking distress. Akhter and Daly (2017) used stock market proxies and T-bond for the Australian banking sector; for macroeconomic determinants of credit risk in the US and Australia, Ali and Daly (2010) used default rates, GDP, six-month T-bill, industrial production and debt-to-GDP ratio; and Illing and Liu (2006) developed a daily financial stress index for the Canada financial system using 11 macroeconomic indicators covering banking, foreign exchange, debt and the equity market. Using macroeconomic indicators to study systemic risk is promising for being able to better map risk and complement bank balance sheet–level data analysis. Using macroeconomic indicators when undertaking systemic risk analysis was suggested by ECB (2009a) to capture two-side interaction between the economy and financial institutions. Our research aims to fill the theoretical gap with an integrated model approach that uses micro- or institution-level data and macroeconomic data to identify SIBs and their effect on systemic risk in the banking system.

1.2 Research Significance

BCBS issued a framework for domestic systemically important banks (D-SIBs) in 2011 and revised this in October 2013. Systemically important financial institutions (SIFIs) exacerbate negative externalities regarding financial system stability. BCBS (2013) admitted that the guideline indicators could not precisely measure specific attributes of SIBs; however, the proxies are designed to identify the central aspect of SIB status. Interlinkages of portfolios and placements among financial institutions creates a connected network where the issue of contagion arises, and the bank network is one of the main focuses in systemic risk study. Financial institutions with more interbank linkages have greater effect on the financial system (Krause & Giansante 2012; Roengpitya & Rungcharoenkitkul 2011). The Century Bank bailout (Indonesian) and Northern Rock case (UK) are examples of small- and medium-sized banks affecting a country's entire economy. Prior research has identified that banks' total assets is insufficient information with which to assess systemic risk. Therefore, our research will elaborate on interbank linkages and map the network using market and balance sheet data to identify SIBs and estimate their effects on the financial system.

Current SIB and systemic risk measure methodologies mostly focus on interconnectedness aspects using publicly available data. ECB (2009a) suggested integrating economy and institutional data to generate a complete picture of risks. Use of macroeconomic indicators to analyse systemic risk is increasing in popularity in response to the 2008 financial crises. However, they are mostly independently estimated as stress test tools or assessed separately from institutional-level data models. Understanding the condition of the economy to address financial contagion will provide regulators and policymakers with a holistic approach. This thesis will combine the network structure model and macroeconomic indicators to assess SIBs from a two-sided interaction (micro and macro perspective). The outputs of this will be practically useful for regulatory bodies to identify SIBs and their effects on the financial system.

1.3 Research Objectives and Questions

This study's objectives are to:

1. Identify SIBs or SIFIs using the Basel indicator-based method. This is the first step towards understanding the developed theoretical models, types of data used, econometric approaches and context. Comprehension of established market model methods will allow us to compare their results with the prudential guideline used by policymakers and bank supervisors.
2. Map the risk escalation and network structure of systemic linkages in the financial system. Systemic risk attracts the attention of regulatory bodies because contagion means a SIFI's failure affects the entire system. Interconnectedness as the consequences of financial activities is suggested by many researchers as a key avenue by which to mitigate financial crises.
3. Identify relevant macroeconomic indicators to analyse SIBs and their effects on the financial system. Crises could be triggered by macroeconomic shocks and market volatility, and identifying representative indicators and statistical procedures is crucial for building a comprehensive model.
4. Estimate and incorporate macroeconomic indicators and micro-level bank data into assessment of SIB methodology. This will ensure a holistic approach to systemic risk assessment, comprised of micro and macro risk.
5. Recommend policies to regulatory authorities for SIB assessment and systemic risk monitoring.

This research will examine how macro and micro indicators affect bank systemic risk. More specifically, we will investigate the following questions:

1. What banks or financial entities are systemically important based on the market model and Basel indicators? The market model will employ CoVaR (Adrian & Brunnermeier 2016), marginal expected shortfall (MES; Acharya, Engle &

Richardson 2012) and SRISK (Brownlees & Engle 2017). BCBS (2018) is the benchmark guideline and will be used to investigate the findings of the market model.

2. What are the key banks or financial entities in the financial system interlinkages network? This study follows Billio et al.'s (2012) proposal to assess risk escalation and variance co-movement using PCA. Financial institutions' importance in the network will be assessed using Granger centrality.
3. What macro and micro indicators affect bank financial/systemic risk? We will select indicators based on previous empirical findings such as Oet et al. (2013); Ali and Daly (2010); Hollo, Kremer and Lo Duca (2012); Illing and Liu (2006); Hakkio and Keeton (2009) and de Mendonça and Silva (2018).
4. How can the identified macro and micro indicators be integrated into a network model for the global context? We will explore global panel data, with reference to recent empirical studies such as de Mendonça and Silva (2018); Mayordomo, Rodriguez-Moreno and Peña (2014); and Yesin (2013).
5. How well does the global model assess/predict bank financial/systematic risk in a specific country? We use Indonesia as a case study and conduct in-depth analyses.

1.4 Thesis Organisation

This thesis comprises eight chapters.

Chapter 1: This chapter introduces the research context; details the research significance, objectives and questions; and outlines the thesis's structure.

Chapter 2: This chapter reviews the extensive literature relevant to this study. It begins with the standards guideline issued by policymakers, which is used as the benchmark in subsequent chapters. The chapter then discusses various aspects of systemic risk models and taxonomy, macroeconomic indicators related to systemic risk, and the Indonesian economy and banking sector.

Chapter 3: This chapter consists of four sections, presenting the chosen research methodology, data type and source, samples and estimation models. This provides the foundation for the analyses in later chapters.

Chapter 4: This chapter presents the extensive modelling of SIBs based on three theoretical approaches (CoVaR, MES and SRISK). The market model results will be compared with the Basel indicator-based results. This chapter answers the first research question.

Chapter 5: In this chapter, using Indonesian capital market data (share price, asset returns and balance sheet data), we estimate the variance decomposition, risk escalation and risk direction of shocks propagation. PCA is used to investigate the results. The importance of banks in the network is estimated using Granger centrality measure. The resulting SIB shortlist is then compared to the Basel interconnectedness score ranking. This chapter answers the second research question.

Chapter 6: This chapter undertakes the same analysis as Chapter 5 using US datasets and covering a longer period to include numerous financial crises. We use a tailored approach in this chapter due to the more detailed statistics. The discussion enhances our comprehension of asset returns co-movement and provides a base for answering the fifth research question.

Chapter 7: This chapter explores the connection of macro and micro granular data. It starts with determining SIBs based on CoVaR, MES and SRISK, following the analysis in Chapter 4. The analysis is carried forward to identify the systemic risk indicated by certain macroeconomic variables. The chapter proposes a systemic risk framework upgrade and technical calculation integration for a holistic approach to systemic risk estimation, both of which can be used by policymakers and regulators. This chapter answers the third and fourth research questions, and contributes to answering the fifth research question.

Chapter 8: This chapter summarises the discussions and findings in prior chapters, including their theoretical and practical implications. The chapter also suggests future research directions.

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Chapter 2: Literature Review

Studies on systemic risk encompass many aspects, and scholars generally use a narrow definition of systemic risk to limit the variables used in their research. Conversely, regulators' definitions of systemic risk and associated terms usually do not explicitly refer to certain variables or causes. For example, ECB (2009a) defines systemic risk as the risk of financial instability so widespread that it impairs the functioning of a financial system to the point that economic growth and welfare suffer materiality; the Reserve Bank of Australia (2014) defines systemic risk as the risk of financial system disruption so widespread or severe that it causes, or is likely to cause, material damage to the economy; and the FSB, IMF and BIS (2009) simply refer to systemic risk as resulting from negative externalities. In academic research, the narrowing of definitions is mostly related to the research scope. For example, De Bandt and Hartmann (2000) define systemic risk as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. Others define systemic risk as arising from the implications of imbalances (Caballero 2010) or correlated exposures (Acharya et al. 2017) to any set of circumstances that threaten the stability of public confidence in the financial system (Billio et al. (2012). Various indicators are considered by regulators and researchers when assessing systemic risk (Bengtsson, Holmberg & Jonsson 2013).

Systemic risk is a result of the interconnectedness of the financial system, resulting from banks' efforts to maintain their liquidity, mitigate risk and transfer risks to their counterparts. 'Too big to fail' banks, SIBs or SIFIs often have multinational operations across different jurisdictions, making supervision challenging. Moshirian (2012) highlights the importance of managing liquidity risk and creating supervision of the global financial system to minimise regulatory arbitrage by large financial institutions. The absence of an effective global supervisory system means access to banks' financial data requires efforts in multiple jurisdictions. Multinational banks have greater ability to use regulatory arbitrage and bypass various national regulations due to the differing regulations and levels of development in countries' financial systems. As a response to the 2008 financial crises, BCBS issued a G-SIBs guideline in 2011, which was updated in 2013. At the press release, BCBS admitted that the process of identifying systemic importance is an ongoing process and still in the early stage of development.

2.1 Standards Guideline on Systemically Important Banks

In 2011, BCBS issued the first standard for regulators to assess G-SIBs (BCBS 2011). These standards were updated in 2013 and 2018 (BCBS 2013, 2018). The rationale for adopting additional policy measures for G-SIBs is based on the 'negative externalities' created by SIBs, which current regulatory policies do not adequately address (BCBS 2012). Although BCBS admitted that the indicators do not precisely measure the specific attributes of SIBs, the proxies are designed to identify the central aspect of SIB status. Indicators of G-SIBs according to the most recent BCBS guideline are shown in Table 2.1.

Table 2.1. Indicator-based Measurement Approach

Category and weighting	Individual indicator	Indicator weighting
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio	20%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Securities outstanding	6.67%
Substitutability/financial institution Infrastructure (20%)	Assets under custody	6.67%
	Payment's activity	6.67%
	Underwritten transactions in debt and equity markets	6.67%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale securities	6.67%

Source: BCBS (2013).

The BCBS G-SIBs guideline categorises bank activities into five main groups consisting of 12 indicators. To make reports comparable between BCBS member countries, banks' data are converted to euros using the exchange rate published on the BCBS website. To calculate the score for a given indicator, a bank's reported value for the indicator is divided by the corresponding total sample (BCBS 2014). For the purpose of creating the list of G-SIBs, the guideline takes the most significant 75 banks as determined by the Basel III leverage ratio exposure measure. The current BCBS guideline calculations use simple ratios that show no linkages between financial institutions and, in practice, give no clear indications for us to predict the adverse effect of SIBs' failure on the financial sector. In response, researchers have proposed alternative methods, variables, assumptions and SIB proxies to measure systemic risk and its effect on the whole economy. The most recent BCBS G-SIBs methodology added trading volume indicator under the substitutability category (BCBS 2018).

BCBS allows some departure from the BCBS (2012) guideline for domestic regulators to better capture specific D-SIBs characteristics and country externalities. For our research in the Indonesian context, the formulae composition is adjusted and rearranged following POJK No. 2/POJK.03/2018 (OJK 2018). The SIB assessment indicators after this adjustment are shown in Table 2.2.

Table 2.2. Basel and Adjusted Indicators

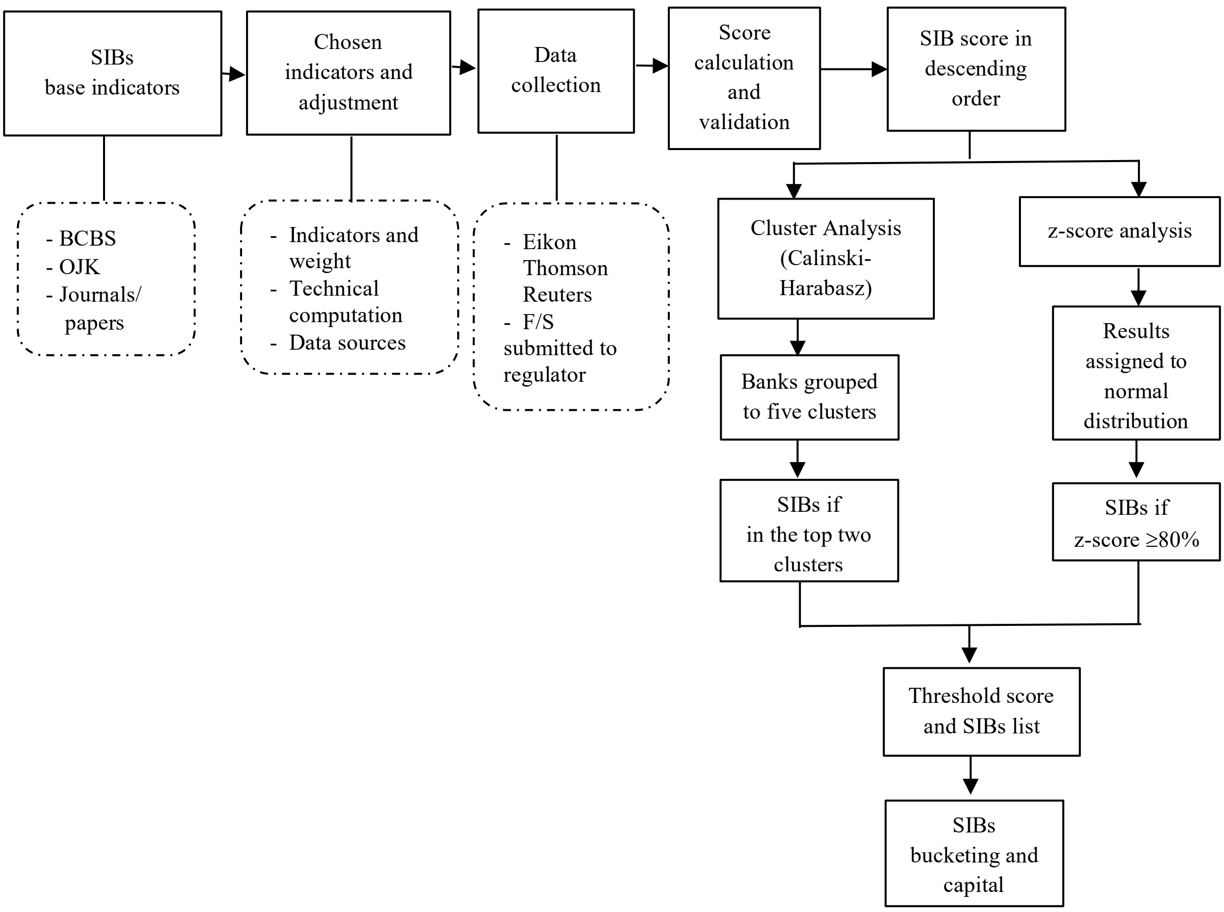
BCBS (2018) Indicators			**OJK (2018) Adjusted Indicators**		
Category (weighting)	*BCBS G-SIBs*	*Indicator weighting*	*Category (weighting)*	*Adjusted indicators D-SIBs*	*Indicator weighting*
Size (20%)	Total exposures	20%	Size (33.3%)	Total exposures	100%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Interconnectedness (33.3%)	Intra-financial system assets	33.3%
	Intra-financial system liabilities	6.67%		Intra-financial system liabilities	33.3%
	Securities outstanding	6.67%		Securities outstanding	33.3%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	Complexity (33.3%)	Notional amount of over-the-counter (OTC) derivatives	25%
	Level 3 assets	6.67%		Trading and available-for-sale securities	25%
	Trading and available for sale securities	6.67%		Domestic indicators	25%
				Substitutability (payment system and custodian)	25%
Substitutability (20%)	Assets under custody	6.67%			
	Payment activity	6.67%			
	Underwritten transactions in debt and equity markets	3.33%			
	Trading volume	3.33%			

BCBS (2018) Indicators			**OJK (2018) Adjusted Indicators**		
Category (weighting)	*BCBS G-SIBs*	*Indicator weighting*	*Category (weighting)*	*Adjusted indicators D-SIBs*	*Indicator weighting*
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%			
	Cross-jurisdictional liabilities	10%			

Source: OJK (2018).

As shown in Table 2.2, we note that OJK, the Indonesian banking authority, simplifies the assessment and uses the discretionary room provided by BCBS. Some of the changes are simplifying the substitutability category indicator and adding domestic indicators to reflect risks posed by domestic banking institutions. The domestic indicators comprise six items: outstanding bank guarantee, irrevocable L/C, government bonds, third parties' funds, loans to third parties and number of bank branches. The work process and assessment workflow, as stipulated by the OJK (2018), is presented in Figure 2.1.

Figure 2.1. Assessment Workflow



Source: Author adapted from OJK (2018).

2.2 Methods of Assessing Systemic Risk

Studies on SIBs and systemic risk are classified based on their statistical measures, methodologies, variables, and financial institutions network interactions. Bisias et al. (2012) summarised recent research based on supervisory scope, research methodology, data perspectives in the main text and presented concise definitions of each risks measurement to include required inputs, expected outputs and data requirements. They classified systemic risk research into five major categories:

1. *Probability distribution*—the most direct measure of systemic risk. Examples of research in this category include the multivariate density function used by Segoviano and Goodhart (2009), who measured dependencies among bank probabilities of default through linear and non-linear dependencies between banks in the banking system as a whole; Adrian and Brunnermeier (2016), who proposed a CoVaR to calculate the VaR of banks and its risk effect on other banks when the financial system is under stress; Acharya Engle and Richardson (2012) and Acharya et al. (2017), who calculated MES and SES to measure financial institutions' expected losses when the market falls below some predefined threshold over a given time horizon; and Brownlees and Engle (2017), who introduced SRISK to capture the expected capital shortage of a firm given its degree of leverage and marginal expected shortfall as the expected loss an equity investor in a financial firm would experience if the overall market declined substantially.
2. *Contingent claims and default*—measures the likelihood of default of each institution and their link to the financial system through joint distribution. Examples of this type of research include Jobst and Gray (2013), who used this approach to propose systemic contingent claim analysis as the generalisation of the option pricing theory pioneered by Black and Scholes (1973) and Merton (1974), and Hermanto and Ayomi's (2014) study to identify the probability of default for over 30 banks in Indonesia during 2002–2013.
3. *Illiquidity*—measurement of banks using the samples of supporting research. Examples include Jobst (2014), who modelled the systemic risk-adjusted liquidity that combines option pricing with market information and balance sheet data to generate a probabilistic measure of the frequency and severity of multiple entities experiencing a joint liquidity event, and Brunnermeier, Gorton and Krishnamurthy (2012), who used bank liquidity position to assess their impact on system-wide net liquidity under the scenario of systemic risk during the financial crises.

4. *Network analysis*—measures the connectedness between banks and the effects of their failure on other banks and the financial system. Research in this category includes Cont et al. (2013), who analysed individual Brazilian banks' balance sheet and network structure in 2007–2008 and failed banks' contribution to systemic risk (using a metric for the systemic importance of institutions named the Contagion Index); Kolari and Sanz (2016), who utilised neural network mapping technology to assess the dynamic nature of systemic risk from 2003–2012 of the 16 largest US banks (they combined the nonparametric statistics method with self-organising maps, which allow visual identification and can assist regulators to identify and monitor safe, cautionary and unsafe banks); Krause and Giansante (2012), who developed a model of interbank loans given and received by banks of different sizes, finding that the size of a failing bank has limited effect on the number of banks affected by contagion and concluding that the bank's network structure has a much more significant effect on systemic risk; Elsinger, Lehar and Summer (2006b), who analysed the network analysis correlated exposure and mutual credit relation that may cause domino effect; and Elsinger, Lehar and Summer's (2006a) research on the extended model used by Eisenberg and Noe (2001) to include uncertainty to quantify the correlated exposure and domino effect.
5. *Macroeconomics* model—Bisias et al. (2012) state few systemic risk scholars use this method to predict bank failure. Based on our reading, although not specifically measuring SIBs and their contribution to systemic risk, some researchers apply macroeconomic variables related to banking distress prediction. Ali and Daly (2010), studying macroeconomic determinants of credit risk in the US and Australia, used default rates, GDP, six-month T-bill, industrial production and debt-to-GDP ratio. Moshirian and Wu (2009) also used leading macroeconomic variables (GDP growth rates, real interest rate, inflation rates, exchange rate, domestic credit growth rates, the ratio of M2 to reserves, and volatility of GDP growth rates) to construct banking industry volatility.

For the purpose of analysis, this thesis will examine the market models using three widely cited and acknowledged models: CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012) and SRISK (Brownlees & Engle 2017). The results of these models will be compared with the Basel indicator-based results. As previously noted, the Basel indicator-based method emphasises institution size, and these three models could assist a supervisor in validating and shortlisting SIBs. The popularity of these three models in systemic risk research makes them representative of the theoretical models used in academic studies.

The conceptual theory of ΔCoVaR proposed by Adrian and Brunnermeier (2016) to measure systemic risk was first introduced in 2008 and has been updated several times. The root comes from Jorion's (2007) work on VaR, which represents the most that the bank loses with confidence level $1 - \alpha$. The parameter of α is 1% or 5%, $Pr(R < -VaR_{\alpha}) = \alpha$. CoVaR corresponds to the market returns VaR condition to certain events $C(R_t^i)$ of firms i. CoVaR is the difference of the financial system VaR condition of firm *i* in financial distress and the financial system VaR when firm *i* is in a median state. CoVaR represents the systemic risk contribution of firm *i* to the financial system.

Acharya, Engle and Richardson (2012) used two standards—VaR and expected shortfall (ES)—to measure firm-level risk. ES is the expected loss conditional on the loss greater than the VaR or the average of returns on days when the portfolio's loss exceeds its VaR limit. Acharya et al. (2017) focus on ES rather than VaR, since the latter is not robust in the sense that negative payoff below the thresholds of 1% or 5% are not captured and the sum of two portfolios' VaR could be higher than the sum of an individual VaR.

Building on Acharya, Engle and Richardson (2012), Brownlees and Engle (2017) theorised that the risk contribution of a financial firm to systemic risk is a function of the firm's size, leverage and risk. Using balance sheet and market data, they calculated the expected capital shortfall over a longer period of market decline called the long-run marginal expected shortfall (LRMES). SRISK considers the equity volatility, return distribution, correlation, size and leverage level of firms. SIFIs are ranked according to the highest SRISK, and the total will be the undercapitalisation of the whole financial system. Estimation of capital shortfall uses bivariate daily equity returns of firms and market index, where volatilities follow asymmetric generalised autoregressive conditional heteroskedasticity (GARCH) and dynamic conditional correlation (DCC) processes. To simulate a crisis, the market index is assumed to fall by 40% over six months, and projection, volatilities and correlation change over time to calculate the tail dependence.

From the regulator point of view, the IMF (2009) also classifies systemic risk studies into groups, as exhibited in Table 2.3.

Table 2.3. Taxonomy of Financial Linkages Model

Category	Network simulations	Default intensity model	Co-risk analysis	Time-varying multivariate density, distress dependence, and tail risk
Calibrated using	BIS cross-border interbank exposures data.	Default data from Moody's default risk service.	CDS spreads.	CDS-PoD and/or stock prices.
Outputs	(1) Provides metric on domino effect triggered by distress events, (2) Identify systemic linkages and vulnerable countries/institutions, (3) Quantify potential losses at country/institutional level, and (4) Track potential contagion paths.	(1) Provides metric of potential banking failures through direct and indirect systemic linkages, and (2) Provides probability measure of tail events.	(1) Estimates unconditional and conditional credit risk measures for different quantiles/risk regimes, and (2) Estimates of the effect on conditional credit risk induced by 'source' institutions on 'locus' institutions.	(1) Recovers multivariate density and common distress/joint probability of default, (2) Distress dependence matrix, and (3) Probability of cascade effects triggered by financial institution.
Advantages	(1) Allows identification of SIB within the system, and (2) Can be used to elaborate 'risk maps' of contagion effects.	(1) Capture effects of direct and indirect linkages among financial institutions, As well as the regime-dependent behaviour of default rates.	(1) Captures co-dependence risk, and (2) Can be used to elaborate 'risk maps'.	(1) Able to use other PoDs, (2) Multiple outputs, and (3) Linear and nonlinear dependence, and (4) Endogenous time-varying distress dependence.

Source: IMF (2009).

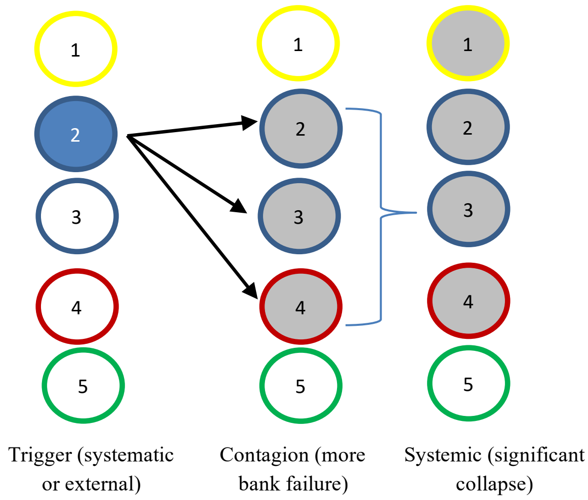
As can be seen, there are several ways to identify SIBs and predict systemic risk, and each method has advantages, required data input and expected outputs. In our research, for the country-specific analysis, we use Indonesia interbank exposures data to construct risk maps of systemic risk in the country.

2.3 Network Models

Exploration of correlated exposure within networks of financial institutions predates the 2008 global financial crises. Intercorrelated exposures are common in the operational activity of financial institutions. Banks, as the key financial institutions in most countries, have intra-financial assets and liabilities to source liquidity need and to invest excess funds in other institutions. During normal economic conditions, the transactions follow the supply and demand mechanism under a competitive financial market. Problems arise due to disruptions stemming from either unsystematic internal failures or external shocks (such as the Asia financial crisis in

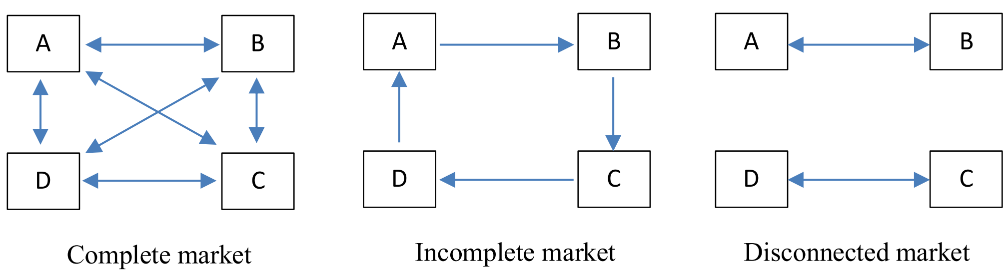
1997 and global financial crises in 2007–2008). Theoretically, financial products' interactions create a complex network that could trigger systemic failure due to the degree of interconnectedness (see Figure 2.2). The failure of one important bank in the network could arise from trading activities, poor risk management, moral hazard, or fraud, and might trigger financial distress to its counterparts. The systematic risk posed by a bank's insolvency is increased if the required capital buffer is lower than the distressed bank's losses. Intercorrelated exposures within the banking system and its effects on the economy provide the basis for policymakers and scholars to develop network models of systemic risk.

Figure 2.2. Financial Contagion Illustration



Allen and Gale (2000) discuss the possibility of contagion and explain how the incompleteness of risk allocation structure within the system could cause systemic failure. They found that a complete structure of proof is more robust than an incomplete one, as exhibited in Figure 2.3.

Figure 2.3. Market Structure



Eisenberg and Noe (2001) modelled the cyclical interdependence using a mechanism that shows how clearing vectors exist, are multidimensional and depend on several aspects. The findings became a trigger for exploring interconnectedness based not only on the size of institutions but also the dispersion within the network itself. The results suggest that using change in total assets values to measure the importance of financial institutions during crises can be misleading. Gai and Kapadia (2010) show how financial systems feature a robust-yet-fragile tendency, where the probability of systemic failure might be low but the effect could be severe.

The bank solvency is $(1-\emptyset)\,A_i^{IB}+qA_i^{M}-L_i^{IB}-D_i>0$ or the equation in the other form $\emptyset<\frac{K_i-(1-q)A_i^{M}}{A_i^{IB}}\ for\ A_i^{IB}\neq 0$, where $K_i=A_i^{IB}+A_i^{M}-L_i^{IB}-D_i$ is the capital buffer. For the crisis to spread to other banks in the system, $\frac{K_i-(1-q)A_i^{M}}{A_i^{IB}}<\frac{1}{j_i}$. Bank with in-degree j is vulnerable with $v_j=P\left[\frac{K_i-(1-q)A_i^{M}}{A_i^{IB}}<\frac{1}{j}\right]$, where $j\geq 1$, and the joint degree distribution of a vulnerable bank is $G(x,y)=\sum_{j,k} v_j\,.\,p_{jk}\,.\,x^j\,.\,\mathrm{y}^{\mathrm{k}}$.

The interbank assets of one bank will equal the interbank liabilities of its counterpart. That is, average in-degree $(1/\mathrm{n})\sum_i j_i=\sum_{j,k} jp_{jk}$ equals average out-degree $(1/\mathrm{n})\sum_i k_i=\sum_{j,k} kp_{jk}$. Therefore, $z=\sum_{j,k} j\,p_{jk}=\sum_{j,k} k\ p_{jk}$. $G(x,y)$ for the link disperse from a random chosen vulnerable bank is:

$$G_0(y)=G(1,y)$$
$$=\sum_{j,k} v_j\,.\,p_{jk}\,.\,\mathrm{y}^{\mathrm{k}}$$
$$G(1{,}1)=G_0(1)$$
$$=\sum_{j,k} v_j\,.\,p_{jk}$$

For the financial instability that does propagate, they define $v_j.r_{jk}$ as the degree of distribution of a random vulnerable bank. Many in-degree or links to one bank will increase the probability jp_{jk} for it to be a network counterpart of the chosen bank. The number of outgoing placements leaving a randomly chosen bank vulnerable bank is:

$$G_1(y)=\sum_{j,k} \quad v_j.r_{jk}.y^k \ =\frac{\sum_{j,k} \quad v_j\cdot j\cdot p_{jk}\cdot y^k}{\sum_{j,k} \quad j\cdot p_{jk}}$$

Gai and Kapadia’s (2010) model is more practical for bank supervisors or policymakers, as they have the privilege to access banks’ detailed data. The advantage of using balance sheet data is that it clearly shows the interconnectedness network between banks. Application could also prompt an increased capital buffer for related banks. Several chapters of this thesis investigate important financial institutions within a financial system network using capital market data.

Another strand of the network model approach uses the market or publicly available data, for example, Billio et al. (2012); Fang et al. (2018); and Baek, Cursio and Cha (2015). Such studies use high-frequency data and PCA as an adaptive descriptive statistic. PCA is used to measure the degree of interconnectedness of asset returns of financial institutions into orthogonal factors of decreasing explanatory power. The PCA focuses on subset n < N, where this set includes most of the volatility during crises and indicates the increase of interconnectedness among the banks. This identifies the contribution $PCA_{i,n}$, of institution *i* to systematic risk.

Another econometric approach to model the linkage of network is using Granger centrality. Application of Granger builds on its ability to predict the forecast of value based on other time series past information. In the capital market where frictions exist, Granger causality appears in the assets return based on other institutions' returns, indicating the spillover risk (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020; Zheng & Song 2018):

$$(j \to i) = \begin{cases} 1 & \text{if j Granger causes i} \\ 0 & \text{otherwise} \end{cases}$$

The interconnectedness measures consist of:

- *Degree of Granger causality* (DGC)—measures the association of N(N–1) pairs of N banks.
- *Number of connections*—captures the importance of banks during the systemic event.
- *Sector-conditional connections*—used to analyse types of entities that affect the other classes.
- *Closeness*—estimates the shortest edges between financial institutions.
- *Eigenvector* centrality—signal of bank significance within the network based on its connection to other banks.

Our thesis employs PCA and Granger centrality as commonly used in financial studies to capture the risk co-movement and escalation. These suit the overlapping exposures that characterise the main operational activities of banks and other financial institutions. The use of PCA and Granger causality can also provide the risk direction, which will assist bank supervisors and policymakers to determine risk spread possibilities.

Diebold and Yılmaz's (2014) model provides another way to map the risk direction of systemic failure in a financial market. Use of this model in our study gives perspective of the spillover risk between entities in a system. The model is based on pairwise direction connectedness from j to i $C^H_{i \leftarrow j} = d^H_{ij}$, where $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i} 1$. Net pairwise $\frac{N^2-N}{2}$ is analogous to bilateral interbank balances. As shown in Table 2.4, total directional connectedness from others to i is defined as $C^H_{i\leftarrow\circ} = \sum_{j=1}^{N} d^H_{ij} \quad j \neq i$, and the opposite of total directional connectedness to others from j as $C^H_{\circ\leftarrow j} = \sum_{i=1}^{N} d^H_{ij} \quad i \neq j$. The grand total off-diagonal entries equivalent of the sum 'from' and 'to' measures of total connectedness is $C^H = \frac{1}{N}\sum_{i,j=1}^{N} d^H_{ij} \quad i \neq j$. Some chapters of this thesis undertake this analysis to compare the results with the Granger results.

Table 2.4. Pairwise Direction of Interconnectedness

	X₁	**X₂**	$\cdots$	**X_N**	**From others**
X₁	d^H_{11}	d^H_{12}	$\cdots$	d^H_{1N}	$\sum_{j=1}^{N} d^H_{1j},\ j \neq 1$
X₂	d^H_{21}	d^H_{22}	$\cdots$	d^H_{2N}	$\sum_{j=1}^{N} d^H_{2j},\ j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
X_N	d^H_{N1}	d^H_{N2}	$\cdots$	d^H_{NN}	$\sum_{j=1}^{N} d^H_{Nj},\ j \neq N$
To others	$\sum_{i=1}^{N} d^H_{i1}$ $i \neq 1$	$\sum_{i=2}^{N} d^H_{i1}$ $i \neq 2$	$\cdots$	$\sum_{i=1}^{N} d^H_{iN}$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1}^{N} d^H_{ij}$ $i \neq j$

2.4 Macroeconomic Indicators of Financial Distress

Studies on SIBs and systemic risk incorporate a mixture of variables, both micro-level or bank balance sheet and macroeconomic data. ECB advised the importance of two-sided interaction between the individual financial institution and the economy:

> a horizontal perspective of systemic risk, where attention is confined to the financial system, and a vertical perspective of systemic risk in which the two-sided interaction between the financial system and the economy at large is taken into account as well (ECB 2009a).

De Bandt and Hartmann (2000) showed few researchers have considered macroeconomic indicators that may be behind contagious default. Since 2000, however, an increasing number of systemic risk academics have used macroeconomic indicators to build the financial stress indexes and model systemic risk. Bisias et al. (2012) listed the macroeconomic indicators used in systemic risk analytics as asset-price boom, property price, macroprudential regulation, GDP stress test, risk topography and several others. From a different point of view but closely linked to banking crises, Moshirian and Wu (2009) employed leading macroeconomic variables (GDP growth rates, real interest rate, inflation rates, exchange rate, domestic credit growth rates, the ratio of M2 to reserves, and volatility of GDP growth rates) to construct banking industry volatility. Then, using the econometric logit model, they tested whether banking industry volatility is a good predictor of banking crises. Other research applying macroeconomic indicators and their relation to banking distress include Akhter and Daly (2017), using stock market proxies and T-bond for Australian banking; and Ali and Daly (2010), on macroeconomic determinants of credit risk in the US and Australia using default rates, GDP, six-month T-bill, industrial production, debt-to-GDP ratio. Some researchers have employed GDP growth as a possible source of systemic risk (Festić, Kavkler & Repina 2011; Hirtle et al. 2016; Schleer & Semmler 2015).

Further, after the turmoil of the 2008 global financial crisis, regulators and policymakers in some countries constructed financial stress indexes to capture the condition of the whole economy using selected macroeconomic indicators. Previous results in this area will be useful for our study, as they identify variables that could be used for SIB assessment. Illing and Liu (2006) developed a daily financial stress index for the Canadian financial system, grouping 11 macroeconomic indicators (covering banking, foreign exchange, debt and the equity market) and analysing them using GARCH estimation to extract volatility measures. Hakkio and Keeton (2009) theorised five financial stress point characteristics: 1) increased uncertainty on the fundamental values of assets, 2) increased uncertainty behaviour of other investors, 3) increased information asymmetry, 4) decreased willingness to hold risky assets or flight to quality and 5) decreased willingness to hold illiquidity assets or flight to liquidity. Based on these, they compiled 11 stress indicators aggregated using PCA to build the Kansas City financial stress index. Hollo, Kremer and Lo Duca (2012) proposed a composite indicator of systemic stress (CISS) to measure financial system stress. They used 15 indicators classified into four economy segments: money market, equity market, bond market and foreign exchange market for the Eurozone. To construct the index, they applied basic portfolio model theory and considered the time-varying cross-correlation between the sub-indices, where CISS put relatively more weight on situations when stress prevailed. Huotari (2015) set up the Finland stress index using some of the financial stress indexes developed by previous studies. Developed stress indexes are summarised in Table 2.5.

Table 2.5. Financial Stress Indexes

Study	Specific stress indicators	Aggregation method	Geographical areas covered
Park and Mercado (2013)	Banking sector beta, exchange market pressure index, stock market volatility, stock market returns, sovereign debt spreads	Variance-equal weighting, principal component analysis	25 emerging and 15 advanced economies
Lo Duca and Pellonen (2013)	TED spread, negative equity returns, stock market volatility, nominal effective exchange rate volatility, three-month government bill yield volatility	Arithmetic average	28 emerging and advanced economies
Cardarelli et al. (2011)	Banking sector beta, TED spread, inverted term spread, corporate bond spread, stock index decline, stock market volatility, real effective exchange rate volatility	Variance-equal weighting	17 advanced economies
Balakrishnan et al. (2009)	Banking sector beta, stock market returns, stock market volatility, sovereign debt spreads, exchange market pressure index	Variance-equal weighting	26 emerging countries
Hakkio and Keeton (2009)	TED spread, two-year swap spread, off-the-run/on-the-run 10-year treasury spread, Aaa/10-year treasury spread, Baa/Aaa spread, HY/Baa spread, consumer ABS/five-year treasury spread, stock and treasury bond correlation, VIX index, and bank stock idiosyncratic	Principle component analysis	US
Illing and Liu (2006)	Banking sector beta, liquidity spread, corporate bond spread, covered interest rate spread, inverted yield curve, weighted dollar crashes, stock market crashes, covered bond T-bill spread	Credit weights	Canada

Source: Huotari (2015).

Additionally, Oet et al. (2013) developed a new hybrid class of models for systemic risk that incorporate the structural characteristics of a financial system. The model was developed using both public and proprietary supervisory data of SIFIs. Using US data from 1991–2011, they divided the sector into:

- Foreign market—financial beta, bond spread, interbank liquidity spread and interbank cost borrowing.
- Foreign exchange market—weighted dollar crash.

- Credit market—interest rate spread, corporate bond spread, liquidity spread and 90-day commercial paper-T-bill spread.
- Equity market—stock market crashes.

Oet, Dooley and Ong (2015) built a financial stress index for Cleveland, US, to identify systemic risk condition. They proposed six market partitions: credit, funding, real estate, securitisation, foreign exchange and equity markets. They selected between several index weighting methodologies across a variety of monitoring frequencies through comparison against a volatility-based benchmark series. MacDonald, Sogiakas and Tsopanakis (2018) applied multivariate GARCH and calculated banking sector variables, money market, equity market and bond market. Assessing the Eurozone economies, they were able to capture the market dependencies and volatilities where the banking and money markets show important stress transmission. The significant of multisector aspects was iterated by Segoviano Basurto et al. (2018) when assessing the systemic risk and interconnectedness using a comprehensive multisector tool called SyRIN. They mapped the interconnectedness channels through the investment fund, hedge fund, insurance and pension fund sectors. A multisector analysis showcased the complexity of systemic risk assessment spanning multiple sectors (Bengtsson, Holmberg & Jonsson 2013).

De Mendonça and Silva (2018) used ΔCoVaR to analyse Brazilian banks from 2011–2015 and highlighted the importance of bank liquidity, profitability, leverage and interest rate to assess systemic risk. They noted that leverage increases systemic risk because banks become more vulnerable to shocks. Additionally, higher returns and increase of monetary policy rate also amplify systemic risk. Conversely, more proportion in liquid total assets could lower systemic risk. Tram and Thi Thanh Hoai (2021) elaborated on the connection of macroeconomics and systemic risk using SES and regressing it using ordinary least square (OLS), REM, FEM and SGMM. Using 29 Vietnam financial institutions' data for 2010–2018, they found that economic growth and interest rate have a positive correlation to systemic risk and exchange rate has a negative correlation to systemic risk. Ramos-Tallada (2015) elaborated on the characteristics of bank lending channels to monetary shocks such as external finance premium and the money market rate in combination with micro banks' granularity like liquidity ratio, capital ratio, size and foreign ownership. He concluded that lending supply is significantly sensitive to money market rate and external finance premium more sensitive to monetary shocks after crises. Laséen, Pescatori and Turunen (2017) assessed the effect of interest rate on systemic risk and welfare employing the New Keynesian model. They found that monetary tightening policy surprise by raising interest rates does not necessarily reduce systemic risk when the financial sector is fragile.

It is known that various blocks of systemic risk variables from macroeconomics should be considered like an exchange rate. Glasserman and Loudis (2015), in their comparison of US and international G-SIBs using the BCBS guideline, found that US banks dominate the complexity and substitutability categories. In that study, the score does not reflect the risk-based capital ratios. Further, fluctuations in exchange rate can significantly affect the score. Some studies highlight the importance of exchange rate to SIFI score (e.g., Mayordomo, Rodriguez-Moreno & Peña 2014; Yesin 2013).

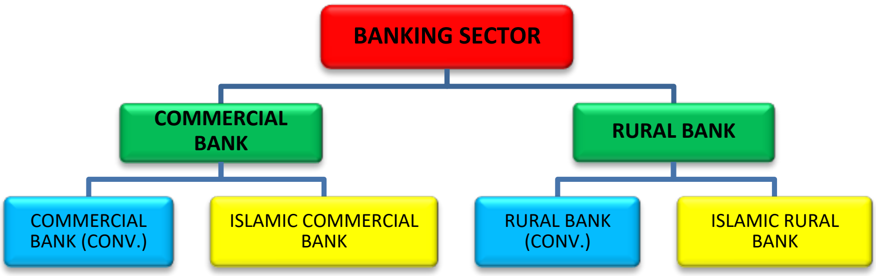
As shown above, since De Bandt and Hartmann (2000) found that few academics use macroeconomic variables in systemic risk analysis, those variables are now increasingly used to predict financial distress (Huotari, 2015). Results from previous financial stress studies provide valuable insights for selecting macroeconomic indicators to complement banks' data and construct the proposed integrated SIB analysis. The importance of the multisector aspect and their relevant indicators as representative in the model are also made apparent. Further, the literature shows the importance of GARCH to detect the volatility of these various variables. The superiority of GARCH was supported by Hansen and Lunde (2005) in their study comparing the performance of 330 ARCH-type models using DM – $ exchange rate data and daily IBM return data.

2.5 The Indonesian Banking Sector

In addition to SIB assessment in a global context, our study will also undertake a country-level assessment using Indonesian banking data. Indonesia was selected due to the country's economic importance, it being an emerging economy in Asia and a member of the G-20. The Indonesian banking system is also appealing to explore, with over 110 registered commercial banks of varying sizes.

In accordance with Banking Act No. 7/1992, as amended by Act No. 10/1998, the Indonesian banking sector is divided into two mainstream banking systems: commercial banks and rural banks (see Figure 2.4). Commercial banks, with diversified products and activities, are the key player in the Indonesian banking sector and account for over 93% of market share (see Table 2.6). Rural banks, with limited products and activities primarily in payment systems, are designed by law to serve micro to small enterprises and provide lending to people in rural areas. Although there are over 1,600 rural banks in Indonesia, they hold less than 2% of banking assets. Further, Indonesian banking activities can be separated into conventional banking and Sharia or Islamic banking (see Figure 2.4).

Figure 2.4. Indonesian Banking Sector Structure



Note: Conv. = conventional.

Table 2.6. Indonesian Banking Sector Market Share

No.	Category	No. of Banks	No. of Offices	Asset (IDR)	Market share (%)
1	Commercial banks (conventional)	118	32,963	5,836,321	93.50
2	Rural banks (conventional)	1,637	5,100	101,713	1.63
3	Sharia commercial banks	34	2,301	296,262	4.75
4	Sharia rural banks	163	446	7,739	0.12
Total		**1,952**	**40,810**	**6,242,035**	**100**

Source: Author calculations.

The Indonesian banking sector is concentrated around 10 big banks. As shown in Table 2.7 and Figure 2.5, these banks hold over 88% of the country's total banking assets. From the regulator's (Otoritas Jasa Keuangan [OJK]) standpoint, to supervise and regulate this industry is difficult, given the diversity in bank size and activities. OJK should be able to manage SIB issues comprehensively and mitigate economic risks by considering the systemic risk posed by SIBs.

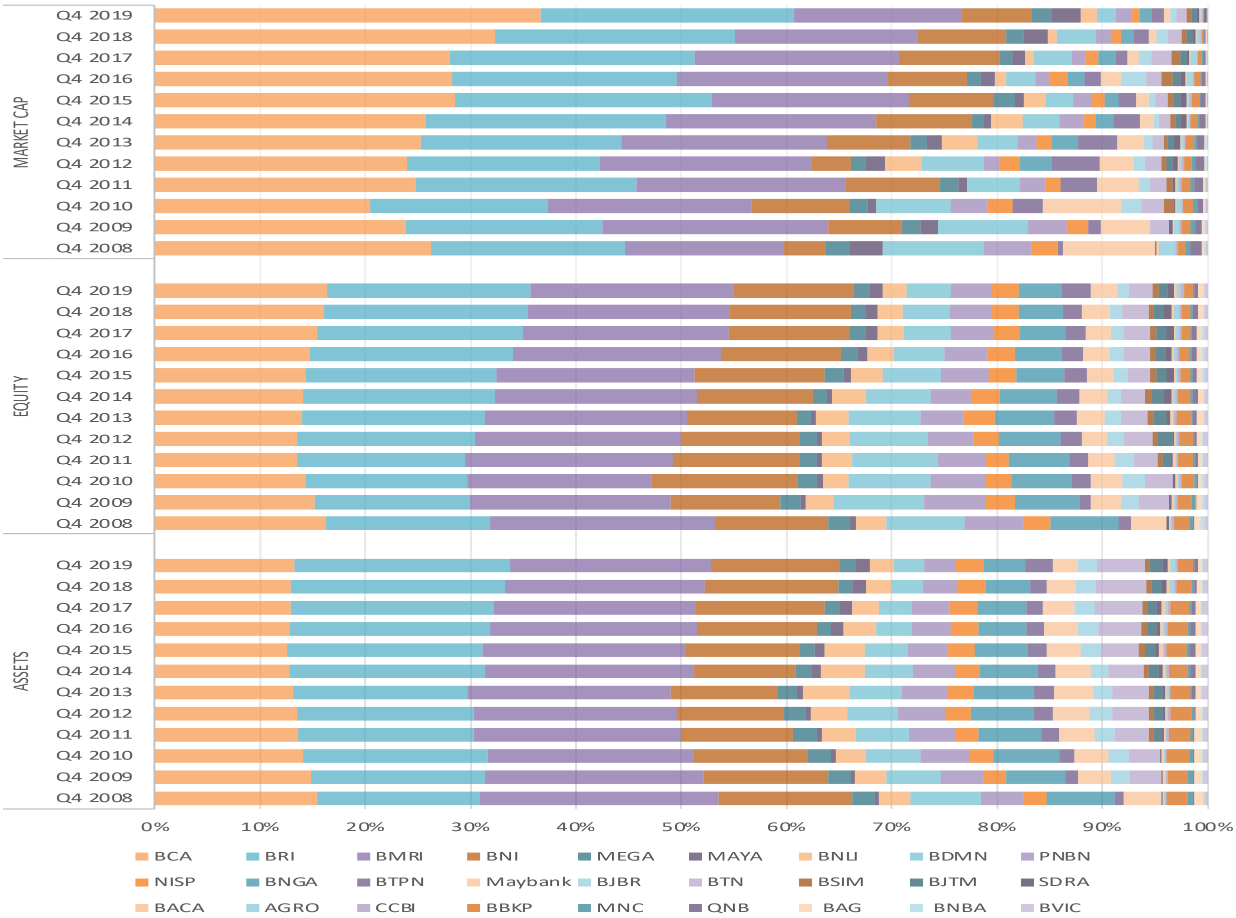
Table 2.7. Thirty Largest Indonesian Banks

No.	Bank	Assets	% of Bank Sector Assets	Third Parties Funds	% of Third Parties Funds	Credit	% of Credit
1	PT. Bank Rakyat Indonesia(Persero), Tbk	1,236,322.87	15.96%	898,040.40	16.71%	804,397.68	15.61%
2	PT. Bank Mandiri (Persero), Tbk	1,042,041.83	13.46%	739,486.53	13.76%	718,966.85	13.95%
3	PT. Bank Central Asia, Tbk	813,968.72	10.51%	630,094.95	11.73%	537,914.43	10.44%
4	PT. Bank Negara Indonesia (Persero), Tbk	756,133.08	9.76%	544,659.54	10.14%	483,665.76	9.38%
5	PT. Bank Tabungan Negara (Persero), Tbk	308,497.11	3.98%	230,266.40	4.29%	237,757.82	4.61%
6	PT. Bank CIMB Niaga, Tbk	266,005.44	3.43%	190,733.50	3.55%	186,513.79	3.62%
7	PT. Pan Indonesia Bank, Tbk	189,236.58	2.44%	130,814.74	2.43%	136,248.16	2.64%
8	PT. Bank OCBC NISP, Tbk	173,582.91	2.24%	125,560.45	2.34%	117,408.47	2.28%
9	MUFG Bank, Ltd	166,163.48	2.15%	39,598.96	0.74%	110,506.54	2.14%
10	PT. Bank Maybank Indonesia, Tbk	163,860.84	2.12%	117,964.55	2.20%	118,938.09	2.31%
11	PT. Bank Danamon Indonesia, Tbk	159,589.09	2.06%	109,557.18	2.04%	104,571.75	2.03%
12	PT. Bank Permata, Tbk	152,759.61	1.97%	117,965.59	2.20%	106,285.95	2.06%
13	PT. BPD Jawa Barat danBanten, Tbk	114,865.32	1.48%	81,609.36	1.52%	74,986.55	1.45%
14	PT. Bank HSBC Indonesia	108,732.88	1.40%	54,906.97	1.02%	68,486.42	1.33%
15	PT. Bank UOB Indonesia	103,694.92	1.34%	77,251.30	1.44%	73,936.75	1.43%

No.	Bank	Assets	% of Bank Sector Assets	Third Parties Funds	% of Third Parties Funds	Credit	% of Credit
16	PT. Bank DBS Indonesia	91,484.69	1.18%	61,785.95	1.15%	56,849.01	1.10%
17	PT. Bank Bukopin, Tbk	90,968.51	1.17%	71,612.23	1.33%	62,016.37	1.20%
18	PT. Bank Tabungan Pensiunan Nasional, Tbk	90,788.84	1.17%	63,232.60	1.18%	60,859.62	1.18%
19	PT. Bank Sumitomo Mitsui Indonesia	88,000.45	1.14%	28,128.51	0.52%	65,109.13	1.26%
20	PT. Bank Mayapada International, Tbk	86,999.72	1.12%	71,510.28	1.33%	65,669.81	1.27%
21	Citibank NA	83,494.41	1.08%	58,525.29	1.09%	49,892.77	0.97%
22	PT. Bank Mega, Tbk	83,164.66	1.07%	60,731.67	1.13%	42,243.70	0.82%
23	PT. BPD Jawa Tengah	67,033.02	0.87%	45,108.69	0.84%	45,899.03	0.89%
24	Standard Chartered Bank	63,364.51	0.82%	29,872.25	0.56%	32,236.08	0.63%
25	PT. BPD Jawa Timur	62,730.30	0.81%	50,915.93	0.95%	33,892.83	0.66%
26	PT. Bank Mizuho Indonesia	61,603.11	0.80%	23,081.74	0.43%	45,135.69	0.88%
27	PT. Bank ICBC Indonesia	55,089.47	0.71%	30,588.04	0.57%	37,277.23	0.72%
28	PT. BPD DKI	53,748.02	0.69%	37,293.25	0.69%	34,699.64	0.67%
29	PT. Bank KEB Hana Indonesia	46,300.42	0.60%	25,148.59	0.47%	35,261.43	0.68%
30	Bank of China (Hongkong) Limited	36,509.91	0.47%	22,475.52	0.42%	17,174.93	0.33%
	TOTAL	**6,816,734.72**	**88.02%**	**4,768,520.96**	**88.75%**	**4,564,802.28**	**88.56%**

Source: Author calculations.

Figure 2.5. Financial Highlights and Market Size of Indonesia's 27 Largest Banks



Note: Bank abbreviations on the y-axis are IDX tickers.
Source: Author calculations.

OJK, as the Indonesian banking system regulator, issued POJK No. 2/POJK.03/2018 to provide the guidelines of SIB supervision and capital surcharge absorbency to safeguard the negative externalities of SIBs (OJK 2018). This regulation copied the BCBS standards, though changes were made to suit domestic conditions (BCBS 2012). For our research, the guidelines of the SIB assessment in POJK No. 2/POJK.03/2018 assist us in constructing the SIB assessment model, as the guidelines require banks publicly disclose their monthly balance sheet data.

Despite Indonesia's economic size and its large number of banking institutions, few studies have examined systemic risk in Indonesia's banking sector. Hermanto and Ayomi (2014) applied the Merton model to identify the probability of default for over 30 banks in Indonesia for 2002–2013. They identified the role of financial linkages across banks by calculating CoVaR (A|B), meaning the CoVaR of bank 'A' is conditioned towards bank 'B' when the financial system is under distress condition. They found bigger banks contributed more to systemic risk. Wijaya, Utama and Kusuma (2015) assessed 77 commercial banks using published financial statement reports between 2006 and 2013. They used Altman z-score as an indicator of individual bank soundness. Interconnectedness among banks was sourced from the interbank placement current account, while deposits from non-banks were used to measure bank dependence to market. The results showed that the average z-score predicted bank soundness as the result of the change in interbank placement.

Muharam and Erwin (2017) estimated the CoVaR of the nine biggest banks in Indonesia through quantile regression. They found that the magnitude of an individual bank's risk is not proportional to the bank's systemic risk contribution. Additionally, the total assets of a bank is insufficient information to assess its contribution to the systematic risk of the banking system. Zebua (2011) investigated Indonesian systemic risk used CAMEL ratios and the CoVaR concept of Adrian and Brunnermeier (2016). They found that the VaR ranking of each bank has a low correlation to overall banking systemic risk level. Further, they revealed that financial linkages or interconnectedness among banks has strong correlation to their contribution to banking systemic risk. The limited research on Indonesia SIBs and systemic risk to date prompts our research to fill the theoretical gaps.

Several prior studies provide useful foundations for our country-level analysis of Indonesia. Wibowo (2017) assessed the effect of capital buffer and leverage on Indonesian banks' systemic risk. That study used Merton distance to default measure and concluded that banks' capital buffer lowers systemic risk effect if the bank's leverage is much lower than its capital buffer. Salim and Daly (2021) recently modelled Indonesia SIBs using CoVaR, MES and SRISK. They demonstrated intertheoretical model correlation and approximated the ranking results with Basel indicator-based methodology, as used by policymakers. Koesrindartoto and Aini (2020) regressed bank characteristic to systemic risk using VaR, MESh, MESdcc and LRMES. Muhajir et al. (2020) developed joint default probability index using the copula approach, Raz (2018) employ z-score and Delta-CoVaR to estimate idiosyncratic and systemic risk, and Hermanto and Ayomi (2014) applied the Merton model to identify the probability of default for over 30 banks in Indonesia for 2002–2013.

OJK has established a Coincidence Index to assess pressures on the financial market on an ongoing basis. This was developed based on Hollo, Kremer and Lo Duca (2012) and has undergone several modifications, with the latest iteration being the 3.0 version. The index divides the pressure into five segments:

- Money market—bid ask spreads of five-year CDS and 10-year bond yield.
- Capital market—market index (IHSG) and market returns volatility (1 month)
- Interbank money market—JIBOR overnight.
- Exchange rate—exchange rate (IDR/USD) and implied volatility.
- Financial block—probability of default.

Additionally, OJK has set an early warning system surveillance platform to estimate cyclical financial sector distress in future. The newest version calculates several leading indicators: banking (non-core liabilities and banking total loan), monetary (central bank reserve and five-year CDS), real economy (commodity price, consumer, business and benchmark index).

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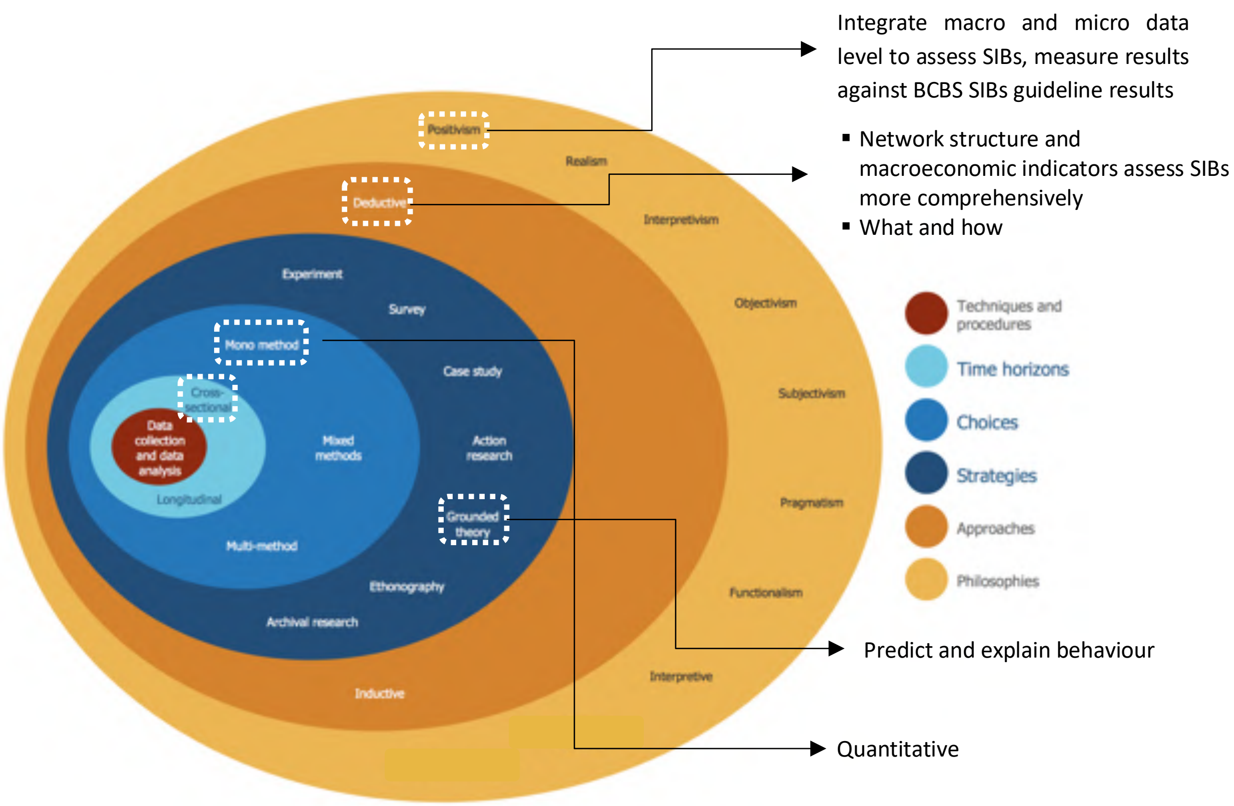
Chapter 3: Research Methodology

3.1 Methodology

Creswell (2014) classified three types of research methods: quantitative, qualitative and mixed. Our research used the quantitative method, involving predetermined hypotheses, data collection and statistical procedures to infer conclusions. Figure 3.1 presents a research onion diagram (Saunders, Lewis & Thornhill 2019) of our research methodology. The research adopted a positivism perspective, proposing to integrate macro and micro granular data for SIB assessment and testing the outcomes against the standards issued and utilised by policymakers.

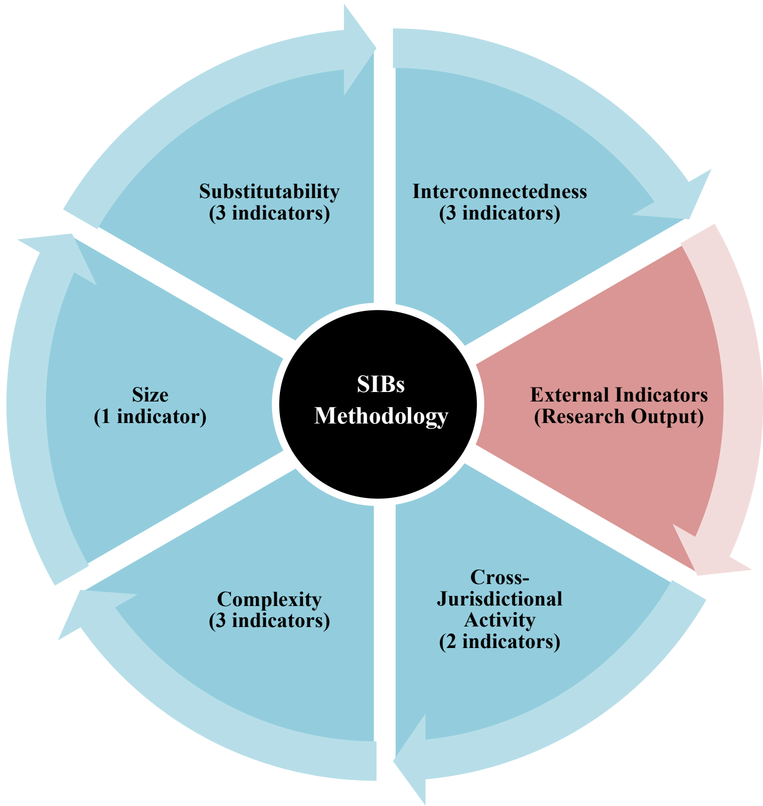
Figure 3.1. Onion Diagram of Research Methodology



Source: Adapted from Saunders, Lewis and Thornhill (2019).

The research outcomes will contribute to better, more holistic systemic risk monitoring. Figure 3.2 summarises how the study will improve SIB assessment by integrating technical considerations into the assessment. BCBS (2018) and OJK (2018) only consider financial entities' internal indices (e.g., total assets) and fail to consider entity and system connection to macroeconomic shocks. Our research fills the theoretical gaps by generating a method that includes the macroeconomic variables that could trigger systemic failure.

Figure 3.2. Integrated SIB Assessment Method



Source: Author.

3.2 Types and Sources of Data

This research uses secondary data—micro-level or bank balance sheet data and market data (see Table 3.1). The granular bank information submitted by banks to the relevant central bank and/or bank supervisor(s) is periodic and mandatory for all entities. The data format is in accordance with the regulation issued by the relevant policymaker, essentially covering all items in the balance sheet and profit loss report (e.g., interbank assets and liabilities, equity, total assets, total liabilities, income and expenses, and net profit/loss).

This detailed micro-level information is crucial for our research, as we expand on the BCBS (2018) indicator-based methodology to rank SIBs and compare the results with the dominant market models. This data is heavily used in Chapters 4, 5 and 7, which elaborate on the D-SIB ranking and network centrality as we investigate the Indonesian economy and banking sector. This data is sourced from Bank Indonesia and OJK, the chief regulatory and policymaker in the Indonesian financial system.

The market data is publicly available, thus most systemic risk studies use this data. Chapters 4–7 employ this data for analyses directly addressing the research questions. Market data includes exchange rate, capital market index, stock price, trading volume activities, assets market value and liabilities, central bank benchmark rate, overnight interbank lending rate, credit default swap spread, etc. The market data is derived mostly from databases such as Eikon Thomson Reuters and FitchConnect. Chapter 6 utilises US financial institution data compiled by Belluzo (2020) as provided on the GitHub website.

The country-level data windows range from 1) 2008–2019 for the Indonesian data to assess SIFIs, the network structure in Indonesian banks and their effect on the Indonesian financial system and 2) 2002–2019 for the US data to include the numerous financial crises during this period. Software packages such as Stata 17 and MATLAB R2021a were used for analysis.

Table 3.1. Data Summary

Chapter	Data	Case	Type	Range	Sources
4	Balance sheet details	Indonesia	Micro	2008–2019	Bank Indonesia and OJK
	Market data		Macro		Eikon Thomson Reuters
5	Balance sheet details	Indonesia	Micro	2012–2019	Bank Indonesia and OJK
	Market data		Macro		Eikon Thomson Reuters
6	Balance sheet (general)	US	Micro	2002–2019	Belluzo (2020) provided on GitHub website
	Market data		Macro		
7	Balance sheet details	Indonesia	Micro	2008–2019	Bank Indonesia and OJK
	Market data		Macro		Eikon Thomson Reuters

3.3 Samples

Chapters 4, 5 and 7 utilise the Indonesian dataset. The sample of Indonesian banks is detailed in Table 3.2.

Table 3.2. Indonesian Dataset Sample

No.	Ticker	Bank	KBMI group
1	BBCA	PT. Bank Central Asia Tbk.	4
2	BBRI	PT. Bank Rakyat Indonesia (Persero) Tbk.	4
3	BMRI	PT. Bank Mandiri (Persero) Tbk.	4
4	BBNI	PT. Bank Negara Indonesia (Persero) Tbk.	4
5	MEGA	PT. Bank Mega Tbk.	3
6	MAYA	PT. Bank Mayapada Internasional Tbk.	2
7	BNLI	PT. Bank Permata Tbk.	3
8	BDMN	PT. Bank Danamon Indonesia Tbk.	3
9	PNBN	PT. Bank Pan Indonesia Tbk.	3
10	NISP	PT. Bank OCBC NISP Tbk.	3
11	BNGA	PT. Bank CIMB Niaga Tbk.	3
12	BTPN	PT. Bank BTPN Tbk.	3
13	BNII	PT. Bank Maybank Indonesia Tbk.	3

No.	Ticker	Bank	KBMI group
14	BJBR	PT. Bank Pembangunan Daerah Jawa Barat Tbk.	2
15	BBTN	PT. Bank Tabungan Negara (Persero) Tbk.	3
16	BSIM	PT. Bank Sinarmas Tbk.	1
17	BJTM	PT. Bank Pembangunan Daerah Jawa Timur Tbk.	2
18	SDRA	PT. Bank Woori Saudara Indonesia Tbk.	2
19	BACA	PT. Bank Capital Indonesia Tbk.	1
20	AGRO	PT. BRI Agroniaga Tbk.	1
21	CCBI	PT. Bank China Construction Indonesia Tbk.	1
22	BBKP	PT. Bank Bukopin Tbk.	2
23	BABP	PT. Bank MNC Internasional Tbk.	1
24	BKSW	PT. Bank QNB Indonesia Tbk.	1
25	INPC	PT. Bank Artha Graha Internasional Tbk.	1
26	BNBA	PT. Bank Bumi Arta Tbk.	1
27	BVIC	PT. Bank Victoria Internasional Tbk.	1

Per OJK (2021), commercial banks in Indonesia are classified into four groups based on their core capital, as follows:

- KBMI 4—banks with more than Rp 70 trillion in core capital. This group represents the leaders in the Indonesian banking industry, offering various products and activities to consumers. There are four banks in this group: BBCA, BBRI, BMRI and BBNI.
- KBMI 3—banks with core capital ranging from Rp 14–70 trillion. It consists of nine banks: MEGA, BNLI, BDMN, PNBN, NISP, BNGA, BTPN, BNII (Maybank) and BBTN.
- KBMI 2—banks with core capital ranging from Rp 6–14 trillion. It consists of five banks: BJBR, MAYA, BJTM, SDRA and BBKP.
- KBMI 1—banks with core capital below Rp 6 trillion. It consists of nine banks: BSIM, BACA, AGRO, CCBI, BABP, BKSW, INPC, BNBA and BVIC. This group provides basic banking products and services, with less outreach and branches.

Chapter 6 investigates the research hypotheses using US financial institution data. The US sample is classified into four groups: investment banks (IB), commercial banks (CB), insurance companies (IC) and government support entities (GSE). This sample was compiled and provided by Belluzo (2020), with the MS Excel worksheet containing share price (daily), trading volume (daily), market capitalisation (daily), total assets and equity (quarterly), and US macroeconomic indicators (daily). There are 4,689 daily observations for each variable for the period 2002–2019. The sample period includes several major shocks to global financial markets, such as the dotcom bubble (2001–2002), subprime mortgage crisis (2008–2009), European debt crisis (2010–2011), Russian ruble crisis (2014–2015) and stock market selloff (2015–2016). The US sample institutions are listed in Table 3.3.

Table 3.3. US Dataset Sample

No.	Ticker	Institution	Group
1	GS	Goldman Sachs	IB
2	MS	Morgan Stanley	IB
3	BAC	Bank of America	IB
4	C	Citigroup	IB
5	JPM	JP Morgan Chase	IB
6	LEH	Lehman Brothers	IB
7	USB	US Bancorp	CB
8	WFC	Wells Fargo & Co	CB
9	STT	State Street	CB
10	PNC	PNC Financial Services	CB
11	AXP	American Express	CB
12	COF	Capital One Financial	CB
13	BK	Bank of New York Mellon	CB
14	AIG	American International Group	IC
15	ALL	Allstate Corp	IC
16	BRK	Berkshire Hathaway	IC
17	MET	Metlife	IC
18	PRU	Prudential Financial	IC
19	FMCC	Federal Home Loan Mortgage Corp / Freddie Mac	GSE
20	FNMA	Federal National Mortgage Association / Fannie Mae	GSE

3.4 Model Estimation

This thesis employs statistical procedures and models to study SIBs and their systemic risk effects. Different models are used to analyse the datasets in each chapter, according to the research objectives. The statistical and econometric methodologies are detailed below. The selected theoretical/market models are CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012) and SRISK (Brownlees & Engle 2017). All three models are widely cited and used in prior systemic research and representative of the theoretical models used by academics.

3.4.1 CoVaR

The ΔCoVaR concept was proposed by Adrian and Brunnermeier (2016) to measure systemic risk. The first concept was introduced in 2008 and has undergone several updates. The root is Jorion's (2007) VaR study, which represented the most that a bank loses, with confidence level $1 - \alpha$, the parameter of α being 1% or 5%, $Pr(R < -VaR_{\alpha}) = \alpha$.

CoVaR corresponds to the VaR of the market returns condition of certain events, $C(R_t^i)$, of firms i:

$$\Pr\left(R_{mt} \leq CoVaR_t^{m \mid rit} \mid C_{rit}\right) = \alpha$$

.

$$X^t i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i$$

$$X_t^{sysli} = \alpha_q^{sys|i} + \gamma_q^{sysIi} M_{t-1} + \beta_q^{sys|i} x_t^i + \varepsilon_{q,t}^{sys|i}$$

These predict the value of the regression to obtain:

$$VaR_{q,t}^i = \alpha_q^i + \gamma_q^i M_{t-1}$$

$$CoVaR_{q,t}^{sysli} = \alpha'^{sys|i}_q + \gamma'^{sysli}_q M_{t-1} + \beta_q'^{sys|i} x_t^i . VaR_{q,t}^i$$

CoVaR is the difference of financial system VaR condition of firm *i* in financial distress and financial system VaR when firm *i* is in a median state. CoVaR represents the systemic risk contribution of firm *i* to the financial system:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^i + CoVaR_{50,t}^i$$

3.4.2 MES

MES was proposed by Acharya, Engle and Richardson (2012), who used two standards to measure firm-level risk: value at risk (VaR) and expected shortfall (ES). VaR is the most that a bank loses, with confidence level 1 – α, the parameter of α being 1% or 5%:

$$Pr(R < -VaR_\alpha) = \alpha$$

ES is the expected loss conditional on the loss being greater than the VaR or the average of returns on days when the portfolio's loss exceeds its VaR limit:

$$ES_\alpha = - E\, [R/R \leq - VaR_\alpha]$$

Acharya et al. (2017) focus on ES rather than VaR, as the latter is not robust in the sense that negative payoff below the thresholds 1% or 5% are not captured and the sum of two portfolios' VaR could be higher than the sum of an individual VaR.

To calculate the contribution of bank-wide losses into groups or trading desk contribution, the next step is decomposing bank return *R* into the sum of each group's return r_i:

$$R = \sum_i = y_i\, r_i$$

where y_i is the weight of group *i* in the total portfolio. Then:

$$ES = - \sum_i y_i\, E(\, r_i \mid R \leq - VaR\,)$$

The sensitivity of overall risk to exposure y_i to each group *i* is:

$$\frac{\delta ES\alpha}{\delta yi} = E(\, r_i \mid R \leq - VaR\,) \equiv MES_\alpha^i$$

where MES^i is group *i*'s losses or MES when the firm is doing poorly.

3.4.3 SRISK

Following from Acharya, Engle and Richardson (2012), Brownlees and Engle (2017) theorised that the risk contribution of a financial firm to systemic risk is a function of the firm's size, leverage and risk. Using balance sheet and market data, they calculated the expected capital shortfall over longer period of market decline called LRMES. SRISK considers the equity volatility, return distribution, correlation, size and leverage level of firms. SIFIs are ranked according to the highest SRISK, and the total will be the undercapitalisation of the whole financial system:

$$SRISK_{i,t} = E_{t-1}\,(Capital\ shortfall_i \mid Crisis)$$

Estimation of capital shortfall uses bivariate daily equity returns of firms and market index, where volatilities follow asymmetric GARCH and DCC processes. To simulate a crisis, the market index is assumed to fall by 40% over six months, and projection, volatilities and correlation change over time to calculate the tail dependence:

$$CS_{i,t} = kA_{i,t} - W_{i,t}$$

$$CS_{i,t} = k(D_{i,t} + W_{i,t}) - W_{i,t}$$

where:

$W_{i,t}$ = market value of equity

$D_{i,t}$ = book value of debt

$A_{i,t}$ = book value of assets

k = prudential capital fraction which is set to 8%

Based on the above formula, when capital shortfall is negative, firms that have positive or surplus working capital can operate normally, but the opposite holds true when capital shortfall is positive and firms are under distress. Firm capital shortfall causes negative externalities only if it occurs when the whole system is already under distress, the multiperiod market return of period t+1 and t+h as $R_{mt+1:t+h}$ and the systemic event reported when $R_{mt+1:t+h} < C$, where C is the market decline threshold:

$$SRISK_{i,t} = E_t\,(CS_{it+h} \mid R_{mt+1:t+h} < C$$

$$= k\,E_t\,(D_{i,t+h} \mid R_{mt+1:t+h} < C) - (1-k)E_t(W_{it+h} \mid R_{mt+1:t+h} < C)$$

A assumption is made by Brownlees and Engle (2017) when debtors are unable to renegotiate their debts during crises:

$$SRISK_{i,t} = kD_{it} - (1 - k)\ W_{it}\,(1 - LRMES)$$

$$= W_{i,t}\,[kLVG_{it} + (1\text{-}k)\ LRMES_{it} - 1]$$

where:

LVG = leverage ratio $(D_{it} + W_{it}) / W_{it}$

LRMES = average of firm equity returns approximated as 1 – exp (–18 x MES) to represent the expected loss over a six-month period with 40% market fall condition.

The contribution or systemic share of firm *i* SRISK is calculated as:

$$\text{SRISK\%}_{i,t} = \frac{SRISK i,t}{\Sigma j \in J\ SRISK j,t}$$

where J = firms with positive SRISK.

3.4.4 Basel Indicator-Based Approach

The BCBS (2018) indicator-based approach assess institutions based on size, interconnectedness, substitutability, global cross-jurisdictional activity and complexity, with 20% weighting given to each of these categories. A key update in the 2018 guideline was providing domestic regulators with substantial freedom to determine their own measures to better identify D-SIB characteristics and country-specific externalities. Analysis of our Indonesian dataset used the adjusted indicators following POJK No. 2/POJK.03/2018 (see Table 3.4).

Table 3.4. Basel and Adjusted Indicators

BCBS (2018) Indicators			**OJK (2018) Adjusted Indicators**		
Category (weighting)	*BCBS G-SIBs*	*Indicator weighting*	*Category (weighting)*	*Adjusted indicators D-SIBs*	*Indicator weighting*
Size (20%)	Total exposures	20%	Size (33.3%)	Total exposures	100%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Interconnectedness (33.3%)	Intra-financial system assets	33.3%
	Intra-financial system liabilities	6.67%		Intra-financial system liabilities	33.3%
	Securities outstanding	6.67%		Securities outstanding	33.3%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	Complexity (33.3%)	Notional amount of over-the-counter (OTC) derivatives	25%
	Level 3 assets	6.67%		Trading and available-for-sale securities	25%
	Trading and available for sale securities	6.67%		Domestic indicators	25%
				Substitutability (payment system and custodian)	25%

Substitutability (20%)	Assets under custody	6.67%
	Payment activity	6.67%
	Underwritten transactions in debt and equity markets	3.33%
	Trading volume	3.33%
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%

Source: OJK (2018).

As shown in Table 3.4, we note that OJK, the Indonesian banking authority, simplifies the assessment and uses the discretionary room provided by BCBS. Some of the changes are simplifying the substitutability category indicator and adding domestic indicators to reflect risks posed by domestic banking institutions. The domestic indicators comprise six items: outstanding bank guarantee, irrevocable L/C, government bonds, third parties' funds, loans to third parties and number of bank branches. POJK No. 2/POJK.03/2018 provides no details or guidance for weighting the indicators. Therefore, for analysis purposes, we allocate equal weighting to each category indicator. As the final step, after the indicator-based calculation, the results are grouped into five buckets using cluster analysis. The Basel D-SIB assessment process was previously presented in Figure 2.1. Per BCBS (2014), the score value for a given indicator is found by dividing a bank's value by the total of the banking system, with the result conveyed in basis points (bps):

$$\frac{Bank\ indicator}{Sample\ total} \text{ x } 10{,}000 = \text{Indicator score (bps)}$$

To get the scores for all three categories, the scores for indicators under each category are averaged. For example, the interconnectedness score is the average of intra-financial assets, intra-financial liabilities and securities outstanding (see Tables 3.5–3.8).

Table 3.5. Illustration: Interconnectedness Score (Securities Outstanding)

Bank	**Secured debt**	**Senior unsecured debt**	**Subordinated debt**	**Equity market cap**	**Total securities outstanding**	**Securities outstanding score**
A	2,000	4,000	1,000	2,500	9,500	745
B	300	250	100	75	725	57
…	…	…	…	…	…	…
…	…	…	…	…	…	…
Z	50	100	25	50	225	18
Total System	40,000	35,000	18,500	34,000	127,500	10,000

In Table 3.5, Bank 'A's securities outstanding score is the result of each component compared to the country's whole banking system, that is: Secured debt (2,000) + Senior unsecured (4,000) + Subordinated (1,000) + Equity market cap (2,500) / Total in banking wide (127,500) = 745.

Table 3.6. Illustration: Domestic Indicators

Bank	**Bank guarantees**		**Irrevocable L/C**		**Government bonds**		**No. of acct. 3rd party funds**		**No of acct. credit to 3rd party**		**Number of branches**		**Domestic indicators score**
	Nom	*Score*	*Nom*	*Score*	*Nom*	*Score*	*Nom*	*Score*	*Nom*	*Score*	*Nom*	*Score*	
A	7,000	1,400	5,000	1,111	2,000	1,081	15,500	456	19,500	857	1,500	300	868
B	2,000	400	1,050	233	1,000	541	7,500	221	6500	286	570	114	299
…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…
Z	175	35	150	33	150	81	5000	147	3750	165	215	43	84
Total System	50,000	10,000	45,000	10,000	18,500	10,000	340,000	10,000	227,500	10,000	50,000	10,000	10,000

Table 3.7. Illustration: Detail Score

Bank	Size	Interconnectedness			Complexity			
	Total Exposure	*Intra-financial assets*	*Intra-financial liabilities*	*Securities outstanding*	*OTC derivatives*	*Trading & AFS securities*	*Domestic indicators*	*Substitutability*
	100%	**33.3%**	**33.3%**	**33.3%**	**25%**	**25%**	**25%**	**25%**
A	1,732	1,100	965	745	500	707	868	745
B	1,030	254	711	57	725	12	299	57
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
Z	217	98	43	18	0	2	84	7
Total banking	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Table 3.8. Illustration: Systemic Score

Bank	Size 33.3%	Interconnectedness 33.3%	Complexity 33.3%	Total systemic score
A	1,732	937	705	1,125
B	1,030	341	273	548
…	…	…	…	…
…	…	…	…	…
Z	217	53	23	98
Total System	10,000	10,000	10,000	10,000

Bank 'A's final systemic score is derived from: Size (1,732 x 33.3%) + Interconnectedness (937 x 33.3%) + Complexity (705 x 33.3%) = 1,125.

3.4.5 PCA

High-frequency data and PCA as an adaptive descriptive statistic are used in many research fields. PCA has been used to analyse systemic risk in Billio et al. (2012); Fang et al. (2018); and Baek, Cursio and Cha (2015). We follow Billio et al. (2012) in measuring the degree of interconnectedness of asset returns of financial institutions into orthogonal factors of decreasing explanatory power:

R^i = stock return of institutions i, *i=1,....,N,* system aggregate return $R^s = \sum_i R^i$,

$E[R^i] = \mu_i$ and $Var[R^i] = \sigma_i^2$ to have:

$$\sigma_s^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sigma_i\sigma_j\, E\left[z_i\, z_j\right]$$

$$Z_k \equiv \frac{(R^k - \mu_k)}{\sigma_k} \quad k = i, j$$

where z_k is the standardised return of institutions *k* and σ_s^2 is the variance of the system.

If we put λ_k the *k*-th eigenvalue with *N* zero mean uncorrelated variables:

$$\mathrm{E}\left[\zeta_k\zeta_l\right] = \begin{cases}\lambda_k & if\ k = 1\\ 0 & if\ k = 0\end{cases}$$

$$Z_i = \sum_{k=1}^{N} L_{ik}\,\zeta_k$$

where L_{ik} is a factor loading for ζ_k for institutions *i*. Then we have:

$$\mathrm{E}\left[Z_iZ_j\right] = \sum_{k=1}^{N}\sum_{l=1}^{N} L_{ik}L_{jl}\,\mathrm{E}\left[\zeta_k\zeta_l\right] = \sum_{k=1}^{N} L_{ik}L_{jk}\lambda_k$$

$$\sigma_s^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sigma_i\sigma_j L_{ik}L_{jk}\lambda_k$$

We focus on subset n < N, as this set captures most of the volatility during crises and indicates the increase of interconnectedness among banks. If total risk of the system is defined as $\Omega \equiv \sum_{k=1}^{N}\lambda_k$ and $\omega_n \equiv \sum_{k=1}^{N}\lambda_k$, the risk associated with the first principal components is $\frac{\omega_n}{\Omega} \equiv h_n \geq H$. The contribution, $PCA_{i,n}$, of institution *i* to system risk is:

$$PCAS_{i,n} = \frac{1}{2}\frac{\sigma_i^2}{\sigma_s^2}\frac{\vartheta\sigma_s^2}{\vartheta\sigma_i^2} \mid h_n > H$$

$$PCAS_{i,n} = \frac{1}{2}\frac{\sigma_i^2}{\sigma_s^2}\frac{\vartheta\sigma_s^2}{\vartheta\sigma_i^2} \mid h_n \geq H = \sum_{k=1}^{N}\frac{\sigma_i^2}{\sigma_s^2}L_{ik}^2\,\lambda_k \mid h_n \geq H$$

3.4.6 Granger Causality

Using Granger causality (in conjunction with the network approach) builds on its ability to predict the forecast of value based on other time series past information. In the capital market where frictions exist, Granger causality appears in the assets return based on other institutions' returns, indicating the spillover risk (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020; Zheng & Song 2018). We use Granger causality to evaluate the direction of risk spreading in a financial system during crises. Please refer to Billio et al. (2012) for the complete formula description:

$$(j \to i) = \begin{cases} 1 & \text{if j Granger causes i} \\ 0 & \text{otherwise} \end{cases}$$

The interconnectedness measures consist of:

a. *Degree of Granger causality* (DGC)—measures the association of N(N–1) pairs of N banks:

$$DGC \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq 1} (j \to i)$$

b. *Number of connections*—captures the importance of banks during the systemic event:

$\#Out$: $(j \to S)|DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} (j \to i)|DGC \geq K'$

$\#In$: $(S \to j)|DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} (i \to j)|DGC \geq K'$

$\#In + Out$: $(j \leftrightarrow S)|DGC \geq K = \frac{1}{2(N-1)} \sum_{i \neq j}^{N} (i \to j) + (j \to i)|DGC \geq K'$

where S = system, *#Out* = number of banks Granger-caused by institution j, *#In* = number of banks Granger-caused by institution j, and *#In+Out* = the sum of these.

c. *Sector-conditional connections*—used to analyse types of banks that affect other classes:

$\#Out - to - Other$: $\frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left((j|\alpha) \to (i|\beta)\right)|DGC \geq K'$

$\#In - from - Other$: $\frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left((i|\beta) \to (j|\alpha)\right)|DGC \geq K'$

$\#In + Out - Other$: $\frac{\sum \beta \neq \alpha \sum i \neq j \left((i|\beta) \to (j|\alpha)\right) + \left((j|\alpha) \to (i|\beta)\right) \,|DGC \geq K'}{2(M-1)N/M}$

where M = banks KBMI 1–4, *#Out-to-Other* = number of banks KBMI Granger-caused by institution j, *#In-from-Other* = number of banks KBMI Granger-cause institution j, and *#In+Out-Other* = the sum of these.

d. *Closeness*—estimates the shortest edges between financial institutions:

$$C_{jS}|_{DGC \geq K} = \frac{1}{N-1} \sum_{i \neq j} C_{ji} \left(j \xrightarrow{C} i\right) |DGC \geq K'$$

e. *Eigenvector* centrality—signal of bank significance within the network based on its connection to other banks:

$$V_j|_{DGC \geq K} = \sum_{i=1}^{N} [A]_{ji} V_i|_{DGC \geq K'}$$

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Chapter 4: Theoretical Approaches vis-à-vis Prudential Basel Guideline: Systemically Important Banks Assessment

We investigate the D-SIBs ranking association of theoretical approaches: CoVaR, marginal expected shortfall (MES), and SRISK, using Basel indicator-based guidelines as the benchmark. Using market data from Indonesian commercial banks from 2008–2019, we compare the results with the Basel outcome by employing the supervisory data submitted to the regulator. The findings show that all theoretical approaches model have positive associations with the Basel ranking outcome, though the best inline results to the Basel D-SIBs shortlist are only around 47%. SRISK delivers more consistent rankings than CoVaR and MES over the sample period. Regarding inter-theoretical approaches, CoVaR – MES has the highest positive correlation (around 58% similarity in rankings). We recommend that scholars build or extend the estimation model to include bank balance sheet and economy data to better capture the specific risks of SIBs.

4.1 Introduction

Banking crises significantly trigger further financial instability and downturns in economic activity across countries. Research conducted by the Basel Committee on Banking Supervision (BCBS) (2010) revealed that, on average, banking crises occur once every 20–25 years; the exception to this trend is the period after the end of the Second World War until the 1970s and 1980s. According to Reinhart and Rogoff (2013), 34 crises occurred during the last 25 years among BCBS member countries. Other studies by Laeven and Valencia (2013) found similar results, reporting 24 banking crises among BCBS member countries from 1985 to 2009.

The economic cost of the 2008 banking crisis was catastrophic and raised the critique of society considering the amount of bailout and its further impact on the economy. A report issued by the US Government Accountability Office (2013) claimed that the 2008 financial crisis was the most severe crisis since the Great Depression of the 1930s. Furthermore, the BCBS (2010) reported the cost of the banking crises by comparing the GDP trend after the crises compare to the pre-crises GDP trend by which the cumulative losses of the crises could be increased if the losses were estimated in the long term. The financial crises also impacted unemployment, household wealth, and the number of foreclosures. The destructive effects of banking crises have highlighted the importance of precise methodologies for analysing and mitigating subsequent banking crises.

Many efforts have been made to identify systemically important banks (SIBs) and their systemic risk impacts, especially after the 2007–2008 global financial crisis. Nevertheless, no approach has perfectly captured and perfectly measured SIBs because of intricate factors and the fact that banks vary widely in their structures and activities and, therefore, in the nature and degree of the risks they pose (BCBS 2018). Bisias et al. (2012) summarised strenuous attempts from scholars from the supervisory scope, research methodology, and data perspectives in the main text and presented concise definitions of each risk's measurement to include required inputs, expected outputs, and data requirements.

After the pioneering work by Allen and Gale (2000), many papers discussed the vulnerability of the financial systems network spillover. One of the most notable papers was produced by Adrian and Brunnermeier (2016), who proposed a conditional value-at-risk (CoVaR) to calculate the VaR of banks and its risk effect on other banks when the financial system is under stress. In other noteworthy research, Acharya, Engle, and Richardson (2012) proposed systemic expected shortfall using the stock price and credit default swaps (CDSs) spread. Furthermore, Brownlees and Engle (2017) introduced the SRISK method to predict the ranking of financial institutions at various stages of the 2008 financial crisis.

Other researchers, such as Billio et al. (2012), tried to analyse the connectedness using principles component analysis and Granger causality. Meanwhile, Chan-Lau (2010) used balance sheet-based network analysis to evaluate interconnectedness risk in mature and emerging market countries under extremely adverse scenarios. In other work, Jobst (2014) combined the option pricing theory with market information and balance sheet data to quantify an individual institution's contribution to expected losses from system-wide liquidity shortfalls.

Further, some researchers have used the network model in their SIBs analyses. The proponent base assumption of a bank's daily operational and transaction activities with other banks or financial institutions to manage the liquidity and risks through interbank placement, derivatives contracts, bank funding and liabilities, which create a complex network structure within the financial system. Studies using a network model have been conducted by Eisenberg and Noe (2001); Gai and Kapadia (2010), Krause and Giansante (2012); Elsinger, Lehar and Summer (2006a); and Elsinger, Lehar and Summer (2006b). Moreover, alternatives using extreme value theory (EVT) have been used to investigate the contagion risk by, for example, Rocco (2014), Dias (2014), Akhter and Daly (2017), and Daly et al. (2019).

The first official guideline on SIBs was issued by BIS in November 2011 in response to the 2007–2008 global financial crisis (BCBS 2011). The standard was revised in July 2013 and further updated in July 2018 (BCBS 2013, 2018). Based on the current methodology, the G-SIBs score is calculated over selected indicators, which are grouped into categories based on their systemic importance. The score's calculation is relatively simple, as the weight proportion is equally divided into each indicator from the data compiled from micro-level or bank balance sheet data. For country-level jurisdiction assessments, BIS allows the local authorities to make a discretionary adjustment of the principles to capture the country's banking characteristics and negative externalities of the local economy (BCBS 2012).

Though increasing attention has been given to systemic risk, no study has directly compared systemic financial institutions derived from a researcher-proposed model using Basel, empirical closeness, or other significantly different results. Perhaps limitations related to data sources to perform the calculation, research scope and the effort that would be required to gather market and prudential data have prevented researchers from conducting this kind of work. This paper aims to fill this gap by comparing three representative models widely cited by academics to identify SIBs vis-à-vis a Basel indicator-based methodology.

Such an analysis is worthwhile because although the BCBS methodology relies on the simple indicator-based measurement approach, a Basel indicator-based approach is more robust than measurement approaches based on currently available models and methodologies that rely on only a small set of indicators or market variables (BCBS 2018). To generate the SIBs list, we applied three models widely cited by academicians: CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012), and SRISK (Brownlees & Engle 2017).

The empirical evidence identified by each model is then contrasted to the Basel SIBs list results (which serve as a benchmark) in each observation period. The study also reflects on two different data sources used in the analysis – namely, market or publicly available data for the academic model and balance sheets or prudential supervisory data submitted by banks to regulators for the Basel model. The observations are based on the market and balance sheet data reported by Indonesian commercial banks to regulators from 2008–2019.

The findings show that SRISK outperforms CoVaR and MES in terms of D-SIBs ranking stability. All three theoretical approaches have positive Kendall's associations; from 2015–2018, the association ranged from 0–0.47. In other words, the best-performing scholar model achieves the Basel D-SIBs ranking list with 47% accuracy. However, market data alone is apparently insufficient for identifying D-SIBs. Therefore, we recommend that scholars extend their models to include published financial statement data to better capture the specific risks faced by banks or to introduce relevant country economy data into the equation and compare the results against the Basel guideline outcomes.

4.2 Literature Review

4.2.1 Theoretical Approaches on Systemically Important Banks

Studies on systemic risk encompass many aspects, and this topic's immense dimensions reflect the definition stated by the regulator. Policy makers' definitions of systemic risk rarely explicitly refer to specific variables as triggers. For instance, FSB, IMF and BIS (2009) define systemic risk as a risk of disruption to financial services that causes impairments of all or parts of the financial system that can have serious negative consequences for the real economy. Meanwhile, the European Central Bank (2009a) defines systemic risk as the risk of financial instability spreading so wide that it impairs the functioning of a financial system by which economic growth and welfare suffer. The Reserve Bank of Australia (2014) defines systemic risk as the risk of financial system disruption so widespread or severe that it causes (or is likely to cause) material damage to the economy. Finally, Bank Indonesia (2014) defines systemic risk as the potential of instability contagious to multiple or whole financial systems attributable to size, complexity, and interconnectedness as the result of exaggerated procyclicality actions taken by financial institutions. The absence of specific factors defining systemic risk shows the complexities of identifying, measuring and mitigating risk.

Researchers simplify the definition based on the scope of their work. For example, De Bandt and Hartmann (2000) defined systemic risk as a systemic event that strongly affects many financial institutions or markets, thereby severely impairing the general functioning of the financial system. Others have claimed that systemic risk arises as the implications of imbalances (Caballero 2010) and correlated exposures (Acharya et al. 2017) to any set of circumstances that threatens the stability of public confidence in the financial system (Billio et al. (2012). Thus, regulators and researchers should simultaneously consider various indicators to assess the complexity of systemic risk (Bengtsson, Holmberg & Jonsson 2013).

Some studies classified research on SIBs and systemic risk based on the statistical measures, methodologies, variables, and financial institutions' network interactions. Bisias et al. (2012) summarised recent research from the supervisory scope, research methodology, and data and presented concise definitions of each risk measurement to include required inputs, expected outputs and data requirements. They classified systemic risk research into five major categories. First, probability distribution, the most direct measure of systemic risk with research samples under this category, such as the multivariate density function used by Segoviano and Goodhart (2009), who measured dependencies among bank probabilities of default through linear and non-linear dependencies in the overall banking system, Adrian and Brunnermeier (2016) proposed a conditional CoVaR (Value-at-risk) to calculate the VaR of banks and its risk effect on other banks when the financial system is under stress. Other researchers (Acharya, Engle & Richardson 2012; Acharya 2009; Acharya et al. 2017) calculated marginal and systemic expected shortfall to measure financial institutions' expected losses when the market falls below a predefined threshold over a given time horizon.

Second, contingent claims and default and liquidity have been used to measure the likelihood that an institution will default and its link to financial system-wide through joint distribution. Jobst and Gray (2013) used this approach to propose systemic contingent claim analysis (CCA) as the generalisation of the option pricing theory pioneered by Black and Scholes (1973) and Merton (1974). Jobst (2014) proposed the notion of systemic risk-adjusted liquidity, which combines option pricing with market information and balance sheet data to generate a probabilistic measure of the frequency and severity of multiple entities experiencing a joint liquidity event. Similarly, Brunnermeier, Gorton and Krishnamurthy (2012) used bank liquidity position to assess their impact on system-wide net liquidity under the scenario of systemic risk during financial crises.

Third, the network analysis method measures the relationship between banks and the impacts of their failure on other banks and the overall financial system. Allen and Gale (2000) modelled financial contagion as an equilibrium phenomenon and claimed that the possibility of financial contagion depends on the completeness of the structure of interregional claims. In other research, Eisenberg and Noe (2001) developed and algorithm that provides information about the systemic risk faced by individual system firms and qualitative statics for the financial system. Meanwhile, Gai and Kapadia (2010) developed an analytical model of contagion with an arbitrary structure in which financial systems exhibit a robust yet fragile tendency. Gai, Haldane and Kapadia (2011) explored the complexity and concentration of financial linkages giving rise to systemic liquidity crises.

Other researchers, such as Brownlees and Engle (2017), introduced systemic risk measure (SRISK) to capture the expected capital shortage of a firm based on its leverage and MES to determine the expected loss of an equity investor in a financial firm if the overall market declined substantially. Furthermore, Elsinger, Lehar and Summer (2006b) analysed the network analysis correlated exposure and mutual credit relation, which could cause a domino effect. Elsinger, Lehar and Summer (2006a) also considered the extended model used by Eisenberg and Noe (2001) to include uncertainty to quantify exposure and the domino effect. Cont et al. (2013) also analysed the balance sheets and network structures of individual Brazilian banks in 2007–2008 and assessed failed banks' contributions to systemic risk. Meanwhile, Krause and

Giansante (2012) developed a model of interbank loans given and received by banks of different sizes.

Moreover, alternatives based on extreme value theory (EVT) have been used to investigate contagion risk. For example, Rocco (2014) showed a considerable rise in interest in the finance literature. Further, Dias (2014) estimated the tail risk at very high quantiles using a semiparametric estimator for a large number of assets in the American stock market. In other research, Akhter and Daly (2017) explored the degree of contagion risk faced by Australian banks spreading from the G-SIBs. Finally, Daly et al. (2019) investigated contagion risk for the global banking environment using three different distance to risk measures-distance to default, distance to capital, and distance to insolvency.

In contrast, despite the size of Indonesia's economy and number of banking institutions, only few studies have examined Indonesia banking systemic risk. For instance, Hermanto and Ayomi (2014) applied the Merton model to identify the probability of default of over 30 banks in Indonesia from 2002–2013. They determined the role of financial linkages across banks by calculating CoVaR (A|B), which means the CoVaR of bank A is conditioned towards bank B when the financial system is in a state of distress. They found that large banks contributed more to systemic risk than small banks. In a related study, Fadhlan (2015) used Granger causality analysis to investigate 37 listed banks in the Indonesia Stock Exchange. The causal relationship of banks was then used to calculate the degree of Granger causality to resemble the systemic risk. Using panel data from 2008 to 2014, he revealed that the in-degree centrality measures significantly affected the risk of individual banks.

In another study, Wijaya, Utama and Kusuma (2015) assessed 77 commercial banks using financial statement reports published between 2006 and 2013. The authors used Altman Z-score to indicate individual banks' soundness from the banking system stability standpoint. Interconnectedness among banks was sourced from the interbank placement current account, while the deposits from the non-bank sector were used to measure banks' dependence on the market. The results showed that the average Z-score forecast banks' soundness according to changes in interbank placement.

In other research, Muharam and Erwin (2017) estimated the CoVaR of the nine biggest banks in Indonesia through quantile regression. They found that the magnitude of each bank's risk was not proportional to its systemic risk contribution. Additionally, the total assets of each bank were not sufficient to assess its contribution to the banking system. Similarly, Zebua (2011) investigated Indonesia's systemic risk using CAMEL ratios and the CoVaR concept of Adrian and Brunnermeier (2016). The author listed each bank's contribution to the banking systemic risk and stated that the VaR ranking of each bank had a low correlation with the systemic risk level across the entire banking sector. Further, they revealed that the financial linkages among banks are strongly correlated to banks' contributions to banking systemic risk.

4.2.2 Standards Guideline

In 2011, the BCBS introduced the standard for the regulator to assess global SIBs (BCBS 2011). The rationale for adopting additional policy measures for G-SIBs is based on the negative externalities created by SIBs, which current regulatory policies do not adequately address (BCBS 2012). The BCBS agreed to review the framework every three years. Thus, the standard was revised in July 2013, and the latest update was issued in July 2018. Although the BCBS admitted that the indicators do not precisely measure specific attributes of SIBs, the proxies are designed to identify the central aspect of SIBs' status. Furthermore, Basel claims that these indicators are more robust than currently available model-based measurement approaches and methodologies that rely on only a small set of indicators or market variables (BCBS 2018). Based on the most updated guidelines, the indicators of G-SIBs are calculated using the indicators listed in Table 4.1. below.

Table 4.1. BCBS Measurement Approach

Category and weight	Individual indicator	Indicator weight
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio*	20%
Interconnectedness (20%)	Intra-financial system assets*	6.67%
	Intra-financial system liabilities*	6.67%
	Securities outstanding*	6.67%
Substitutability/financial institution Infrastructure (20%)	Assets under custody	6.67%
	Payment activity	6.67%
	Underwritten transactions in debt and equity markets	3.33%
	Trading volume	3.33%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale securities	6.67%

* Extended scope of consolidation to include insurance activities
Source: BCBS (2018).

The Basel G-SIBs guideline framework categorises bank activities into five main groups comprising 13 indicators. The newest standard introduced, among other things, a trading volume indicator, a modification to the weights in the substitutability category, and an extension of the scope of consolidation to insurance subsidiaries (BCBS 2018). The reports between each BCBS member country were compared by converting the banks' data into euros using the exchange rate published on the BCBS website. Furthermore, to calculate the scores of given indicators, the banks' reported values for the related indicator are divided by the corresponding total sample. When creating the list of G-SIBs, Basel considers the most significant 75 banks as determined by the Basel III leverage ratio exposure measure. To bring the G-SIBs context to the country-level jurisdiction, BIS allows local authorities to make discretionary adjustments to the principles to capture the country's banking characteristics and the negative externalities of the local economy (BCBS 2012).

At the country level, Indonesia is a G20 member country gradually rising as one of the world's most significant economies. It is currently the world's eighth biggest economy based on purchasing power parity and it is projected to become the fifth-largest economy by 2030 and the fourth-largest by 2050, after China, India, and the US (PwC 2017).

Despite the country's steady growth (around 5% over the last few years), Indonesia has maintained its debt at around 30% of its GDP and has kept inflation to ± 3% per year. Indonesia's banking system, in accordance with Banking Act No. 7 1992 (as amended with Act No. 10 1998), is divided into two mainstreams which are commercial banks and rural banks. As of December 2018, there were 115 commercial banks and 1,760 rural banks; both numbers reflect the numbers of conventional and sharia banks in the country.

Commercial banks with diversified products and activities are the main players in the Indonesia banking system, of which accounted for more than 98% market share in terms of total assets, sources of funds and distributed funds. Sources of funds include third-party funds, interbank liabilities, loans received, securities issued and spot and derivative liabilities; meanwhile, distributed funds comprise credit, interbank placement, securities, equity investment, impairment of financial assets and spot and derivative claims.

On the other hand, rural banks are relatively small, provide limited products and primarily engage in activities dealing with the payment system and clearing mechanisms. Further, these banks are designed by law to serve micro-small enterprises and lend to people in rural areas. Though there are many of them, they possess slightly more or less than 2% of the national banking assets share.

The Indonesia banking topography is mainly concentrated on the 30 biggest banks in the country. The largest of these possess more than 88% of the country's total banking assets, third-party funds and credit disbursed (see Table 4.2.). In this research, we analyse all the commercial banks listed on the Indonesia Stock Exchange in the theoretical model since the assumption and variables are available as market data. Meanwhile, for the Basel methodology, we analyse all (listed and unlisted) commercial banks in Indonesia using bank data reported to the banking regulator.

Table 4.2. Top 30 Banks as of Dec 2018

No	Banks	Assets	%	3rd Parties Fund	%	Credit	%
1	PT. Bank Rakyat Indonesia(Persero), Tbk	1,236,322.87	15.96%	898,040.40	16.71%	804,397.68	15.61%
2	PT. Bank Mandiri (Persero),Tbk	1,042,041.83	13.46 %	739,486.53	13.76%	718,966.85	13.95%
3	PT. Bank Central Asia Tbk	813,968.72	10.51 %	630,094.95	11.73%	537,914.43	10.44%
4	PT. Bank Negara Indonesia (Persero), Tbk	756,133.08	9.76%	544,659.54	10.14%	483,665.76	9.38%
5	PT. Bank Tabungan Negara (Persero), Tbk	308,497.11	3.98%	230,266.40	4.29%	237,757.82	4.61%
6	PT. Bank CIMB Niaga, Tbk	266,005.44	3.43%	190,733.50	3.55%	186,513.79	3.62%
7	PT. Pan Indonesia Bank, Tbk	189,236.58	2.44%	130,814.74	2.43%	136,248.16	2.64%
8	PT. Bank OCBC NISP, Tbk	173,582.91	2.24%	125,560.45	2.34%	117,408.47	2.28%
9	MUFG Bank, Ltd	166,163.48	2.15%	39,598.96	0.74%	110,506.54	2.14%
10	PT. Bank Maybank Indonesia, Tbk	163,860.84	2.12%	117,964.55	2.20%	118,938.09	2.31%
11	PT. Bank Danamon Indonesia, Tbk	159,589.09	2.06%	109,557.18	2.04%	104,571.75	2.03%
12	PT. Bank Permata, Tbk	152,759.61	1.97%	117,965.59	2.20%	106,285.95	2.06%
13	PT. BPD Jawa Barat dan Banten, Tbk	114,865.32	1.48%	81,609.36	1.52%	74,986.55	1.45%
14	PT. Bank HSBC Indonesia	108,732.88	1.40%	54,906.97	1.02%	68,486.42	1.33%
15	PT. Bank UOB Indonesia	103,694.92	1.34%	77,251.30	1.44%	73,936.75	1.43%
16	PT. Bank DBS Indonesia	91,484.69	1.18%	61,785.95	1.15%	56,849.01	1.10%
17	PT. Bank Bukopin, Tbk	90,968.51	1.17%	71,612.23	1.33%	62,016.37	1.20%
18	PT. Bank Tabungan Pensiunan Nasional, Tbk	90,788.84	1.17%	63,232.60	1.18%	60,859.62	1.18%
19	PT. Bank Sumitomo Mitsui Indonesia	88,000.45	1.14%	28,128.51	0.52%	65,109.13	1.26%
20	PT. Bank Mayapada International, Tbk	86,999.72	1.12%	71,510.28	1.33%	65,669.81	1.27%
21	Citibank NA	83,494.41	1.08%	58,525.29	1.09%	49,892.77	0.97%
22	PT. Bank Mega, Tbk	83,164.66	1.07%	60,731.67	1.13%	42,243.70	0.82%
23	PT. BPD Jawa Tengah	67,033.02	0.87%	45,108.69	0.84%	45,899.03	0.89%
24	Standard Chartered Bank	63,364.51	0.82%	29,872.25	0.56%	32,236.08	0.63%
25	PT. BPD Jawa Timur	62,730.30	0.81%	50,915.93	0.95%	33,892.83	0.66%
26	PT. Bank Mizuho Indonesia	61,603.11	0.80%	23,081.74	0.43%	45,135.69	0.88%
27	PT. Bank ICBC Indonesia	55,089.47	0.71%	30,588.04	0.57%	37,277.23	0.72%
28	PT. BPD DKI	53,748.02	0.69%	37,293.25	0.69%	34,699.64	0.67%
29	PT. Bank KEB Hana Indonesia	46,300.42	0.60%	25,148.59	0.47%	35,261.43	0.68%
30	Bank of China (Hongkong) Limited	36,509.91	0.47%	22,475.52	0.42%	17,174.93	0.33%
	TOTAL	**6,816,734.72**	**88.02%**	**4,768,520.96**	**88.75%**	**4,564,802.28**	**88.56%**

Source: Author calculation.

For the country-level jurisdiction assessment, BIS allows local authorities to make discretionary adjustments to the principles to capture the country's banking characteristics and negative externalities of the local economy (BCBS 2012). In the present research, we construct a preliminary assessment of SIBs based on Basel guidelines and adjust it using bank balance sheet data submitted to Otoritas Jasa Keuangan (OJK). The Indonesia Financial Services Authority (OJK), as the Indonesian banking regulator, issued POJK No. 2/POJK.03/2018 to guide the supervision of SIBs and the capital surcharge absorbency to safeguard the negative externalities of SIBs. After the indicator-based calculation, the SIBs are grouped into five buckets using cluster analysis and Z-score analysis. The capital surcharge and phase-in period for banks to fulfil the capital surcharge are arranged to follow OJK (2018)

4.3 Data and Methodology

4.3.1 Data Source

We use two separate datasets for the CoVaR, MES and SRISK to cover all commercial banks listed in the Indonesia Stock Exchange from 2008–2019. Initially, 33 banks were considered for the model calculation; this number was subsequently reduced to 27 after discarding some banks because of incomplete data or inactive trading. We obtained the market data of Indonesian banks from Eikon Thomson Reuters databases.

For the Basel framework calculation, micro or balance sheet data sourced from monthly reports submitted to the central bank and Indonesia FSA (OJK) are used. This sample covers all 115–120 Indonesian commercial banks. The number of banks varies over time because of mergers and acquisitions during the observation window. For the Basel methodology, the observation windows are assessed twice a year from 2015–2018. The particular time frame with regard to the Indonesia D-SIBs regulations was introduced in 2015 (OJK 2015).

4.3.2 Model Estimation

The theoretical approaches to estimate and analyse the network model are using CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012), and SRISK (Brownlees & Engle 2017). These specific measurement models were chosen because this thesis aims to compare its direct estimation results, using the Basel outcome as the benchmark. The above three models in systemic risk have gained popularity and are widely cited in the systemic risk literature, as it is a good basis for representing the theoretical models used.

4.3.2.1 CoVaR

This model was proposed by Adrian and Brunnermeier (2016) in 2008 and has undergone several updates. VaR is the most that the bank loses with a confidence level 1 - α, where the parameter of α is 1% or 5%, $Pr(R< -VaR_{\alpha}) = \alpha$. CoVaR corresponds to the VaR of the market returns conditions to certain events $C\left(R_t^i\right)$ of firms i.

$$\Pr\left(R_{mt} \leq CoVaR_t^{m\,|\,rit} \;|\, C_{rit}\right) = \alpha$$

$$X^t i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i$$

$$X_t^{sysli} = \alpha_q^{sys|i} + \gamma_q^{sysIi} M_{t-1} + \beta_q^{sys|i} x_t^i + \varepsilon\,_{q,t}^{sys|i}$$

These predict the value of the regression to obtain:

$$VaR_{q,t}^{i} = \alpha_q^i + \gamma_q^i M_{t-1}$$

$$CoVaR_{q,t}^{sysli} = \alpha\,'^{sys|i}_{q} + \gamma'^{sysIi}_{q} M_{t-1} + \beta_q'^{sys|i} x_t^i . VaR\,_{q,t}^{i}$$

CoVaR is the difference between the financial system VaR condition of firm i under financial distress and the financial system VaR when the firm i is in a median state. CoVaR represents the systemic risk contribution of firm i to the financial system-wide.

$$\Delta CoVaR_{q,t}^{i} = CoVaR_{q,t}^{i} + CoVaR_{50,t}^{i}$$

4.3.2.2 Marginal Expected Shortfall (MES)

The model was proposed by Acharya, Engle and Richardson (2012), **who** used two standards to measure firm-level risk; value at risk (VaR) and expected shortfall (ES). VaR is the most that the bank loses with confidence level 1 - α, where the parameter of α is 1% or 5%.

$$Pr(R< -VaR_{\alpha}) = \alpha$$

The ES is the expected loss conditional on the loss being greater than the VaR or the average of returns on days when the portfolio's loss exceeds its VaR limit.

$$ES_{\alpha} = - E\ [R/R \leq - VaR_{\alpha}]$$

Acharya et al. (2017) focus on ES rather than VaR since it is not robust because negative payoffs below the thresholds 1% or 5% are not captured and the sum of two portfolio VaR could be higher than the sum of individual VaR. Further, the next step in calculating the contribution of bank-wide losses into groups or trading desk contribution is todecompose the bank return R into the sum of each group's return r_i. That is $R = \sum_i = y_i\, r_i$ where y_i is the weight of group i in the total portfolio. Then,

$$ES = - \sum_i y_i\, E(\, r_i \mid R \leq - VaR\,)$$

The sensitivity of overall risk to exposure y_i to each group i is calculated as

$$\frac{\delta ES\alpha}{\delta yi} = E(\, r_i \mid R \leq - VaR\,) \equiv MES_{\alpha}^{i}$$

where MES^i is group i's losses or MES when the firm is doing poorly.

4.3.2.3 SRISK

According to Acharya, Engle and Richardson (2012) and Brownlees and Engle (2017), the risk contribution of a financial firm to the systemic risk is a function of its size, leverage, and risk. Using the balance sheet and market data they calculate the expected capital shortfall over longer period of market decline, referred to as *Long-Run Marginal Expected Shortfall* (LRMES).

SRISK considers not only equity volatility, return distribution and correlation but also the size and leverage level of the firms. The systemically important financial institutions are ranked according to the highest SRISK and the total is the undercapitalization of the whole financial system wide.

$$SRISK_{i,t} = E_{t-1}\,(Capital\ shortfall_i \mid Crisis)$$

The estimation of capital shortfall considers the bivariate daily equity returns of firms and market index with volatility, following asymmetric GARCH and DCC correlation processes. When the crisis is simulated, the market index is assumed to fall by 40% over six months, and volatilities and correlations

$$CS_{i,t} = kA_{i,t} - W_{i,t}$$

$$CS_{i,t} = k(D_{i,t} + W_{i,t}) - W_{i,t}$$

where: $W_{i,t}$ = market value of equity

$D_{i,t}$ = book value of debt

$A_{i,t}$ = book value of assets

k = prudential capital fraction which is set to 8%

Based on the formula then when the capital shortfall is negative the firms have positive or surplus working capital and can operate normally. Meanwhile, the opposite is true when capital shortfall is positive, in which case the firms are in distress. A firm capital shortfall causes negative externalities only if it occurs when the whole system is already under distress, in which case the multiperiod market return of period t+1 and t+h as $R_{mt+1:t+h}$ and the systemic event reported when $R_{mt+1:t+h} < C$, where C is the market decline threshold.

$$SRISK_{i,t} = E_t\,(CS_{it+h} \mid R_{mt+1:t+h} < C$$

$$= k\,E_t\,(D_{i,t+h} \mid R_{mt+1:t+h} < C) - (1\text{-}k)E_t(W_{it+h} \mid R_{mt+1:t+h} < C)$$

According to another assumption made by Brownlees and Engle (2017) debtors are unable to renegotiate their debts during the crises,

$$SRISK_{i,t} = kD_{it} - (1-k)\,W_{it}\,(1 - LRMES)$$

$$= W_{i,t}\,[kLVG_{it} + (1\text{-}k)\,LRMES_{it} - 1]$$

where: LVG = leverage ratio $(D_{it} + W_{it}) / W_{it}$

LRMES = average of firm equity returns approximated as 1 – exp (-18 x MES) to represent the expected loss over six-month period conditionally the 40% of market fall.

The contribution or systemic share of firm *i* SRISK is calculated as:

$$SRISK\%_{i,t} = \frac{SRISKi,t}{\Sigma j \in J\ SRISKj,t}$$

where J = firms with positive SRISK.

4.3.2.4 Basel Indicator-Based Approach

The BCBS (2018) indicator-based approach was used to evaluate institution size, interconnectedness, substitutability, global cross-jurisdictional activity, and complexity. The Basel guideline gives an equal proportion of 20% weight into five categories. The departure from Basel guidelines asserted by the BCBS (2012) to better capture specific D-SIBs characters and country externalities. For our dataset, we adjust the formulae composition and re-arrange the indicators following POJK No. 2/POJK.03/2018. The SIBs assessment indicators after country adjustments are presented in Table 4.3. below.

Table 4.3. OJK D-SIBs Indicators

Category and weighting	BCBS G-SIBs	Indicator weighting	Category (weighting)	Adjusted Indicators D-SIBs	Indicator weighting
Size (20%)	Total exposures	20%	Size (33.3%)	Total exposures	100%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Interconnectedness (33.3%)	Intra-financial system assets	33.3%
	Intra-financial system liabilities	6.67%		Intra-financial system liabilities	33.3%
	Securities outstanding	6.67%		Securities outstanding	33.3%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	Complexity (33.3%)	Notional amount of over-the-counter (OTC) derivatives	25%
	Level 3 assets	6.67%		Trading and available-for-sale securities	25%
	Trading and available for sale securities	6.67%		Domestic indicators	25%
				Substitutability (payment system & custodian)	25%
Substitutability (20%)	Assets under custody	6.67%			
	Payment activity	6.67%			
	Underwritten transactions in debt & equity markets	3.33%			
	Trading volume	3.33%			
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%			
	Cross-jurisdictional liabilities	10%			

Source: OJK (2018).

As shown in the table, OJK, as the Indonesia banking authority, simplifies the assessment and use of the discretionary room provided by Basel by adjusting the indicators. Some of the differences make the Basel substitutability category indicator more complex and add domestic indicators to reflect the risks posed by country banking institutions. Further, domestic indicators are composed of six (six) items: outstanding bank guarantee, irrevocable L/C, government bonds, third-parties funds, loans to third parties and number of bank branches. Since POJK No. 2/POJK.03/2018 shows no details on the weighting of the indicators for analysis, we allocate an equal weight to each category of indicators. As the final step, after the indicator-based calculation, the results are grouped into five buckets using cluster analysis. The Basel D-SIBs analysis processes are depicted in the graph. The BCBS (2014) illustrates the sample to obtain the score for a given indicator, and the bank's value is then divided by the total of the banking system; the results are presented as basis points (bps).

4.4 Results

To validate the data integrity and calculation, we grouped data into several excel worksheets based on different variables: shares price, market capitalisation, total assets, total equity, state variables, and sample groups. For share prices, market capitalisation, and state variables (7D repo rate, T-bill delta, credit spread, liquidity spread, TED spread, yield spread, JSX LQ45 excess return, JSX financial sector excess return and JSX VIX), daily data are provided. Other data, such as total assets and total equity, are given on a quarterly basis. The datasets comprise 27 actively traded banks listed in the Jakarta Stock Exchange (JSX) from 2008–2019. The sample banks are listed in Table 4.4. below.

Table 4.4. Bank Sample and KBMI

No.	TICKER	BANK	KBMI
1	BBCA	PT. Bank Central Asia Tbk.	4
2	BBRI	PT. Bank Rakyat Indonesia (Persero) Tbk.	4
3	BMRI	PT. Bank Mandiri (Persero) Tbk.	4
4	BBNI	PT. Bank Negara Indonesia (Persero) Tbk.	4
5	MEGA	PT. Bank Mega Tbk.	3
6	MAYA	PT. Bank Mayapada Internasional Tbk.	2
7	BNLI	PT. Bank Permata Tbk.	3
8	BDMN	PT. Bank Danamon Indonesia Tbk.	3
9	PNBN	PT. Bank Pan Indonesia Tbk.	3
10	NISP	PT. Bank OCBC NISP Tbk.	3
11	BNGA	PT. Bank CIMB Niaga Tbk.	3
12	BTPN	PT. Bank BTPN Tbk.	3
13	BNII	PT. Bank Maybank Indonesia Tbk.	3
14	BJBR	PT. Bank Pembangunan Daerah Jawa Barat Tbk.	2
15	BBTN	PT. Bank Tabungan Negara (Persero) Tbk.	3
16	BSIM	PT. Bank Sinarmas Tbk.	1
17	BJTM	PT. Bank Pembangunan Daerah Jawa Timur Tbk.	2
18	SDRA	PT. Bank Woori Saudara Indonesia Tbk.	2
19	BACA	PT. Bank Capital Indonesia Tbk.	1
20	AGRO	PT. BRI Agroniaga Tbk.	1
21	CCBI	PT. Bank China Construction Indonesia Tbk.	1
22	BBKP	PT. Bank Bukopin Tbk.	2
23	BABP	PT. Bank MNC Internasional Tbk.	1
24	BKSW	PT. Bank QNB Indonesia Tbk.	1
25	INPC	PT. Bank Artha Graha Internasional Tbk.	1
26	BNBA	PT. Bank Bumi Arta Tbk.	1
27	BVIC	PT. Bank Victoria Internasional Tbk.	1

In total, 2,971 daily observations were made for each variable from 2008–2019. However, some data are missing for three-month T Bills; to counter this, we use STATA multiple imputations with 669 verified results before moving on to the next step for model estimation using Matlab R2019b coding developed by Belluzo (2020). A statistics summary of the results is exhibited in Table 4.5.

Table 4.5. Systemic Risk Statistics

	Mean	Min	Max	SD	Variance	Kurtosis
Beta	1.13	.422	1.688	.193	.037	3.533
VaR	3.45e+07	1.18+e07	7.60+e07	1.24+e07	1.536e+14	2.54
ES	8.06e+07	2.51+e07	23.33+e07	2.65+e07	7.037e+14	2.835
CoVaR	7.69e+06	-1.96+e05	6.73+e07	7.95+e06	6.319e+13	10.64
Delta	948.845	260.895	2200.084	409.061	167331.17	2.593
MES	2.67e+07	7.33+e06	6.82+e07	1.09+e07	1.204e+14	2.481
SRISK	4.59e+05	0	2.89+e06	5.85+e05	3.430e+11	3.967

Figure 4.1 presents the systemic averages across three estimation model in a line graph. The ES averages are the highest followed by VaR and MES and CoVaR. Meanwhile, for SRISK, Δ CoVaR has closer values. Furthere, VaR and MES move in the same direction over time and indirectly showed how the MES model developed around the VaR concept.

4.4.1 CoVaR

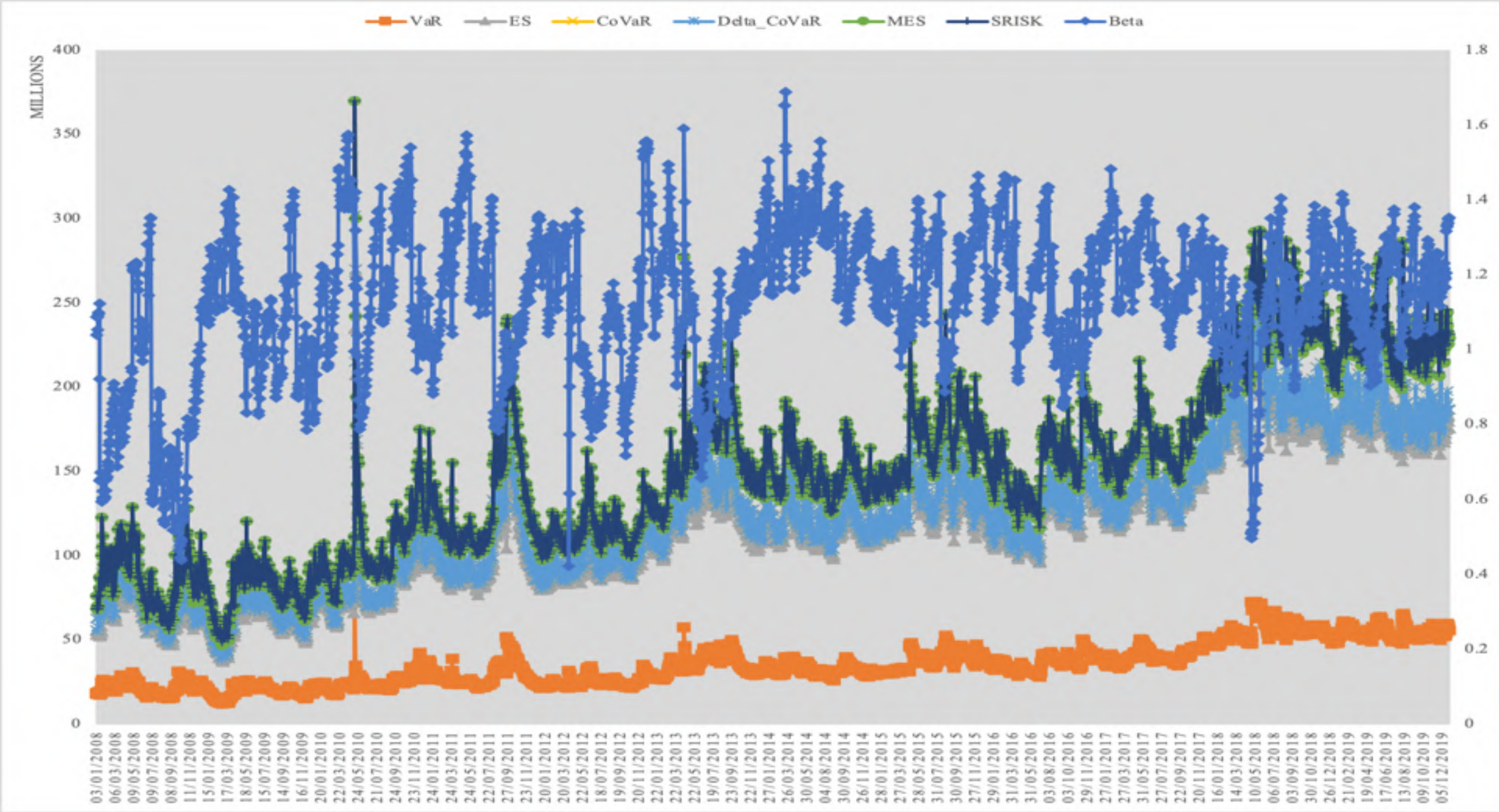
CoVaR systemic risk measure, as introduced by Adrian and Brunnermeier (2016), is rooted in the VaR concept, which stemmed from the work of Jorion (2007) and measures the most that investors can lose over a certain investment horizon. Briefly, ΔCoVaR is the marginal contribution of VaR to the whole financial system during financial crises and the median VaR of the financial system in the normal states. Based on model calculations, the rank of SIBs with contributions greater than 5% from 2016–2019 are listed in Table 4.6. below.

Table 4.6. CoVaR rankings

2016			2017			2018			2019		
Banks	% to system	Rank	Banks	% to system	Rank	Banks	% to system	Rank	Banks	% to system	Rank
BJBR	23.52%	1	BBCA	20.09%	1	BBCA	20.55%	1	BBCA	19.75%	1
BJTM	17.21%	2	BMRI	16.92%	2	BMRI	18.88%	2	BJBR	16.94%	2
BBCA	14.90%	3	BBNI	10.50%	3	BJBR	11.91%	3	BMRI	15.20%	3
BMRI	14.03%	4	BJBR	9.38%	4	BBNI	10.16%	4	BBNI	9.62%	4
BBRI	7.02%	5	BBRI	9.27%	5	BBRI	7.90%	5	BBRI	7.52%	5
BBNI	6.75%	6	BJTM	6.54%	6	BJTM	7.04%	6	BJTM	5.97%	6
									SDRA	5.72%	7

The SIBs rankings remained quite stable over the sample period though the systemic risk contribution change. Based on the full results, the SIBs of four banks were recorded in 2008, while those of seven banks were recorded in 2019. Their systemic contribution to the whole financial system was greater than 5%. The list is also dominated by the Indonesia big banks classified as BKMI 4, which represented a total equity of more than Rp 70 trillion and BKMI 3, with a total equity in the range of Rp 14–70 trillion. See Appendix A-1 for the complete results of calculations over the full sample period.

Figure 4.1. Systemic Risk Average (Left Axis) and Beta (Right Axis)



4.4.2 Marginal Expected Shortfall (MES)

Using the model proposed by Acharya et al. (2017) with a confidence level of 95%, we ranked the banks based on their systemic contributions (Table 4.7).

Table 4.7. MES ranking

2016			2017			2018			2019		
Banks	**% to system**	**Rank**	**Banks**	**% to system**	**Rank**	**Banks**	**% to system**	**Rank**	**Banks**	**% to system**	**Rank**
BBNI	8.33%	1	BDMN	17.08%	1	BBNI	11.22%	1	BVIC	12.75%	1
AGRO	7.94%	2	BBNI	12.23%	2	BBTN	8.08%	2	BBNI	10.36%	2
BBTN	7.27%	3	BBRI	8.14%	3	BMRI	7.33%	3	AGRO	8.88%	3
BJTM	7.01%	4	BBCA	6.27%	4	BVIC	6.96%	4	PNBN	6.88%	4
BDMN	6.03%	5	MEGA	6.16%	5	BDMN	6.83%	5	BDMN	6.05%	5
BBRI	6.01%	6	BMRI	5.83%	6	BBRI	6.36%	6	BBKP	5.82%	6
BBKP	5.78%	7	BBKP	5.06%	7	PNBN	5.99%	7	BBRI	5.77%	7
BMRI	5.58%	8				BBKP	5.95%	8	BMRI	5.5%	8
									BBCA	5.21%	9
									BBTN	5.21%	10

In the scenario of the MES-based model originates from when the crises hit, the shareholders experienced a decline in their assets returns and market value of equity. In line with the crisis scenario, the assumption followed by Acharya et al. (2017) was used, according to which the index fell by more than 40% over the next six months, calculated as LRMES. See Appendix A-2 for the complete results of calculation over the full period of the sample.

The MES ranking results are more distributed but resulted in more banks making systemic risk contributions to the whole financial system compared to the ΔCoVaR results. Based on the same table, more volatile bank rankings were found compared to ΔCoVaR over the sample window periods. According to the MES systemic risk estimation from 2008–2019, the most significant systemic contribution during the sample window period was made by BBRI, which is one of the biggest banks in Indonesia (16.51% recorded in 2008). The appearance of BVIC and AGRO, relatively small banks or BKMI 1, reflect the vulnerability of undercapitalisation during crises and the possibility of capital injection by controlling shareholders. Oppositely, although not at the top of the list in all sample period, BKMI 4 banks consistently appeared at the top, as a relatively low position might have reflected their equity ability to absorb volatilities better than BKMI 1 banks.

4.4.3 SRISK

Brownlees and Engle (2017) offered the SRISK concept to measure the systemic risk that combines the market and balance sheet data that does not solely depend on equity volatilities, returns and correlation. SRISK integrates and complements other systemic estimation models by using bank size and degree of leverage. Total aggregate SRISK resembles the total amount of capital that related parties or governments need to raise in financial crises. SRISK = 0 means that the firms do not need to inject capital in case financial distress hits the economy based on severity assumptions. A negative SRISK signifies that the firms have excess capital to counter and sustain crises. Our sample calculations using SRISK estimation are as follows.

Table 4.8. SRISK Ranking

2016			2017			2018			2019		
Banks	**% to system**	**Rank**	**Banks**	**% to system**	**Rank**	**Banks**	**% to system**	**Rank**	**Banks**	**% to system**	**Rank**
BBTN	28.09%	1	BBKP	52.75%	1	BBNI	40.78%	1	BBNI	49.14%	1
BBNI	26.65%	2	BBNI	26.11%	2	BBTN	28.55%	2	BBTN	20.15%	2
BBKP	13.36%	3	INPC	14.51%	3	BBKP	13.36%	3	BBKP	10.94%	3
BNGA	12.77%	4	BVIC	6.63%	4	BNGA	11.45%	4	BNGA	10.52%	4

The results exhibit the most stable ranking list out of ΔCoVaR and MES over the sample period. The systemic share contribution also could be more concentrated among four banks, with the exception of 2015, when it was distributed among eight banks. Refer to Appendix A-3 for the complete results of the calculations over the full sample period.

As stated earlier, SRISK = 0 means that the banks have enough capital, even during crises with a 40% of market decline and with the prudential capital regulation (CAR) assumed to be 8%. The results also show that, based on the SRISK model, Indonesian banks are mostly in a sound state with zero SRISK, even when faced with financial distress. This situation could also be because of OJK conservatism, as banks' regulatory institutions in Indonesia require banks to have 8–11% of minimum CAR, depending on their risk profile. OJK (2016) also mandated all commercial banks in Indonesia to provide a 2.5% capital conservation buffer plus a 0–2.5% countercyclical buffer. Furthermore, banks in the D-SIBs list must keep an extra 1–2.5% of the capital surcharge.

Based on all three systemic risk measures (ΔCoVaR, MES and SRISK), we test the ranking stability and concordance using Kendall's to find agreement in D-SIB rankings over the sample period. A Kendall's value of agreement is W=1 when there is high agreement and W=0 when there is low agreement. The results inline and confirm our findings. From most to least stable, the measures are ranked as SRISK (0.9674), ΔCoVaR (0.9414) and MES (0.7983).

Ranking stability is important for the regulator to require the D-SIBs to meet capital surcharge once they are put on the shortlist as stated in the Basel guideline.

Paradoxically, the MES ranking has lower stability even if direct and simple estimation calculations are used: Beta (0.8193) and CoVaR (0.8045). Plotting and explore model and variables into the ranking concordance matrix shows that the highest agreement is achieved by MES and Beta (0.65), followed by ΔCoVaR and CoVaR (0.64). The findings show that almost two-thirds of the total MES D-SIBs ranking results were obtained when using the shares Beta and quite the same for CoVaR in terms of generating the ΔCoVaR rankings list. The ranking stability and concordance for all models are displayed in Figure 4.2.

Further, as we derived the correlation matrix, the connection between market models is displayed in Figure 4.3. Based on the figure, SRISK and MES also have a positive correlation, though it is low (0.29). Nevertheless, it resulted in a 50% association in their D-SIBs ranking list. Furthermore, the correlation values for the association between ΔCoVaR and SRISK are positive and relatively low at 0.30, although this translates to a higher ranking concordance of 0.43. Meanwhile, ΔCoVaR and MES have quite a high positive correlation (0.93), but this converts to only 0.58 similarity in D-SIBs rankings.

4.4.4 Basel Indicator-Based Approach

The Basel indicator-based guideline emphasises the size of the institution in proportion to the whole industry. For instance, the interconnectedness sub-indicators reflect a bank's share of interbank assets and liabilities in the system rather than showing how contagious the distress of one institution is to the others through interbank placement transactions. The logical thinking of the Basel methodology is daunting whether researchers could shortlist similar results simply by ranking the institutions using the data in financial statements. Refer to Appendix A-4 for the complete results of SIBs ranking over the full sample period.

Per our research objective to contrast the Basel D-SIBs to the theoretical approaches applied by scholars, we tested correlations at four check points during 2015–2018. Considering the confidential data submitted to the regulator, we code the firms to certain IDs but keep them traceable to make comparisons with the results obtained from theoretical approaches (ΔCoVaR, MES and SRISK).

Figure 4.2. Ranking Stability and Concordance

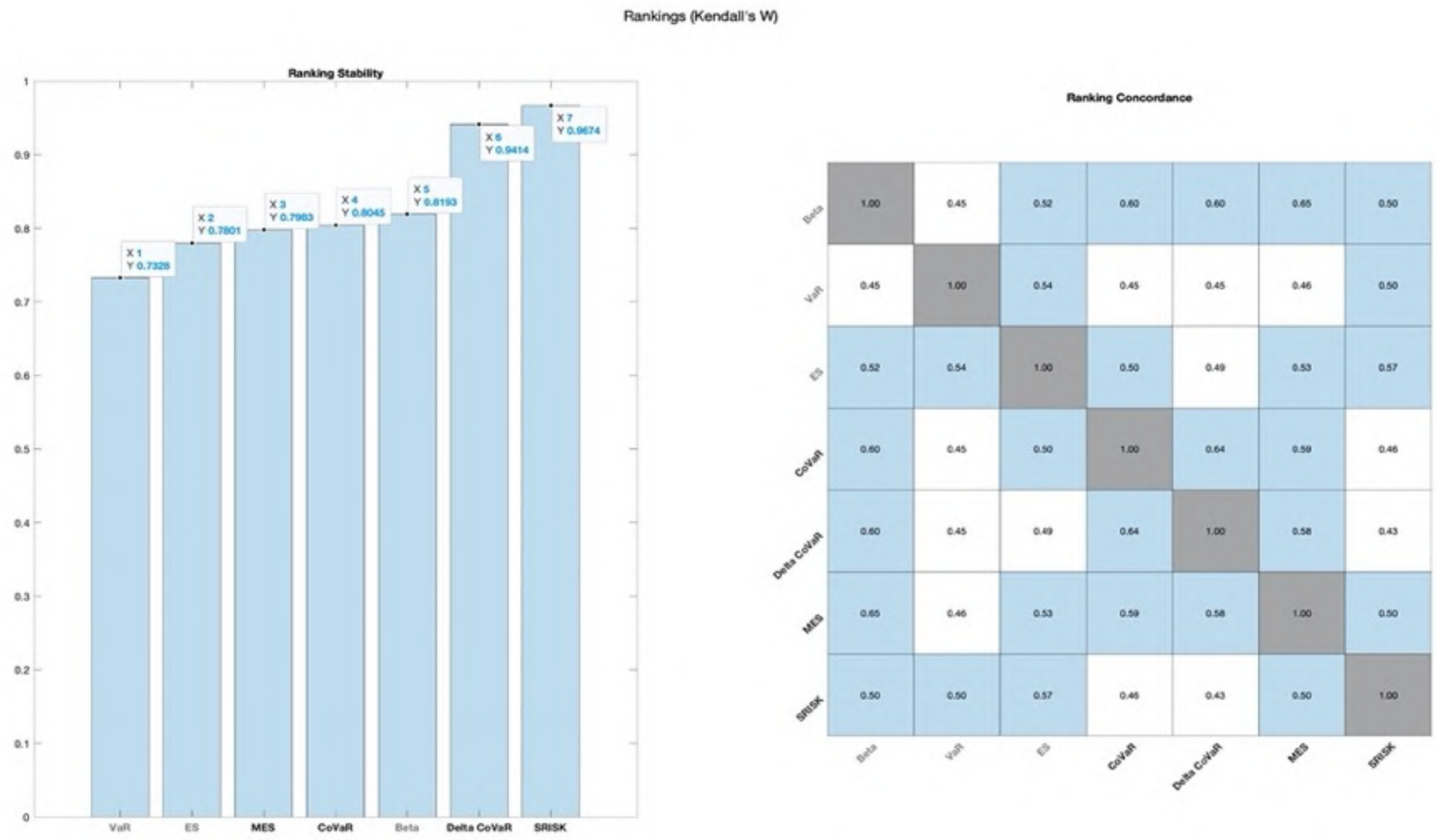
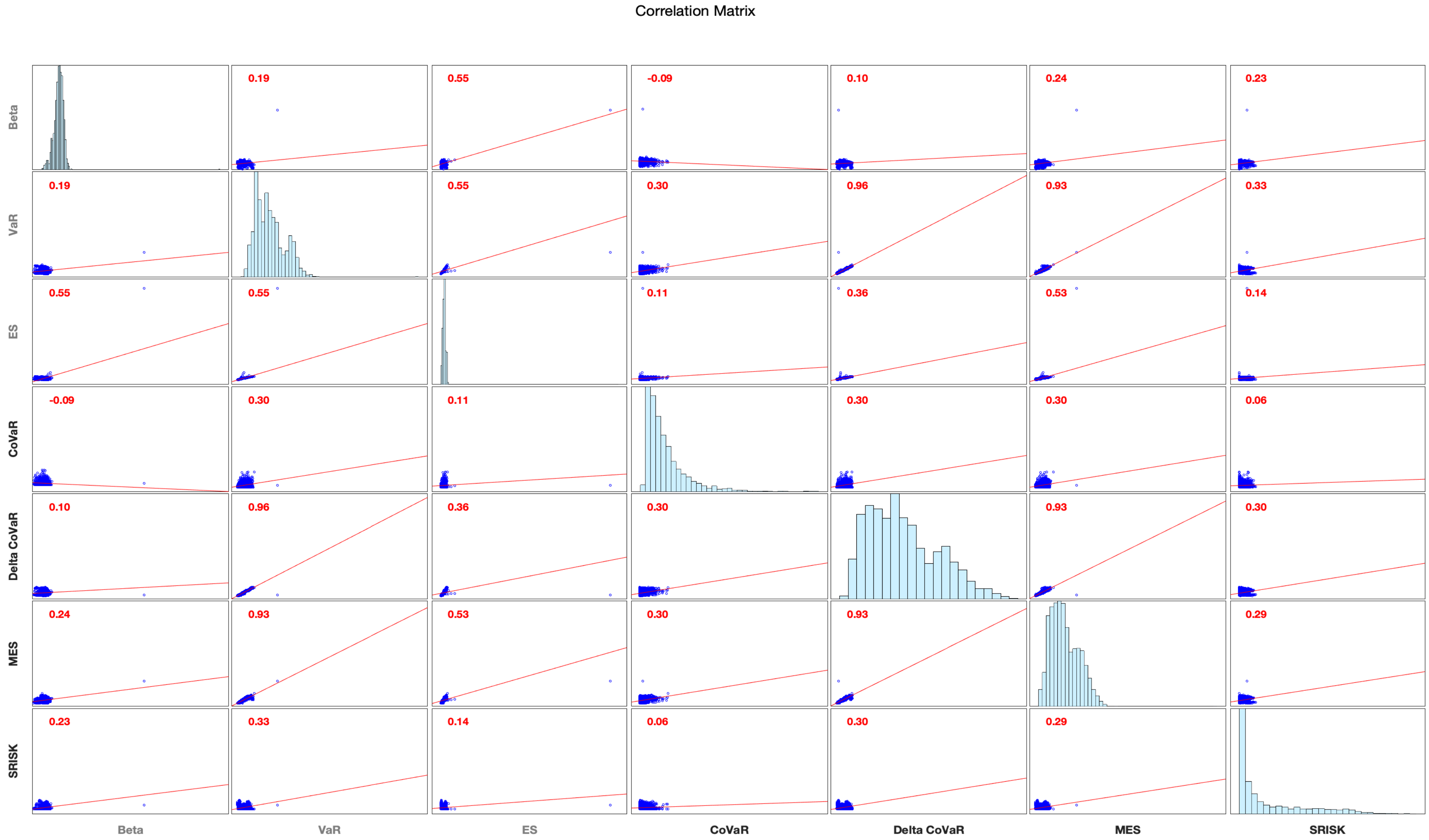


Figure 4.3. Correlation Matrix across Models



Using Kendall's tau non-parametric correlation test, the correlation of theoretical approaches to the Basel indicator is positive (three out of four checkpoints). However, the association number is quite low, ranging from 0–0.47. The strongest association with the Basel ranking list was reported in 2015 using MES (0.47). Further, Kendall's correlation peaked at 0.33 in 2016 when using ΔCoVaR and in 2018 when using SRISK. Moreover, in 2017 the correlations of all theoretical approaches with prudential Basel are weak. The results for Kendall's correlation are served in Table 4.9. The results of Kendall's correlation are displayed in Table 4.9.

To validate Kendall's tau, we run a robustness test using Spearman's Rho correlation in STATA. The outputs are inline aside from numbers, which tend to increase if we use Spearman's Rho. The strength and direction of the ranked banks were highest in 2015 when using MES (0.60), followed by ΔCoVaR (0.40). The SRISK ranking in the same year is contrary to the Basel shortlist (-1.00). In 2016, ΔCoVaR was the closest to Basel (0.40), while SRISK was the closest in 2018 (0.50) according to the robustness test.

4.5 Conclusion

This chapter investigates how closely three widely cited theoretical estimation approaches mimic the Basel prudential methodology used by the regulator to shortlist D-SIBs. Using Indonesia banking data collected from 2008–2019, we run CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012) and SRISK (Brownlees & Engle 2017) to shortlist Indonesian D-SIBs and compare the data to that derived from the prudential Basel ranking list. The findings show that every estimation model used by scholars has distinctive advantages. In terms of D-SIBs ranking stability, SRISK outperformed ΔCoVaR and MES.

All three theoretical approaches have positive Kendall's associations; however, for the checkpoints from 2015–2018, the associations ranged from 0–0.47. In other words, the closest any of the models used by scholars can be expected to come to the Basel D-SIBs ranking is about 47%. Thus, it seems that market data alone is not enough to identify D-SIBs, and we suggest academicians extend their model to include published financial statement data to better capture banks' specific institution-level risks. It would also be interesting to integrate relevant country economy numbers into the equation and compare the results with the Basel guideline outcomes.

Table 4.9. Kendall's Correlation

	CoVaR15	**CoVaR16**	**CoVaR17**	**CoVaR18**	**Mes15**	**Mes16**	**Mes17**	**Mes18**	**Srisk15**	**Srisk16**	**Srisk17**	**Srisk18**	**Bsl15**	**Bsl16**	**Bsl17**	**Bsl18**
CoVaR15	1.0000															
CoVaR16	0.0667	1.0000														
CoVaR17	0.6000	−0.0667	1.0000													
CoVaR18	0.7333	0.0667	0.8667	1.0000												
Mes15	−1.0000	−1.0000	−0.6667	−0.6667	1.0000											
Mes16	−0.4000	−0.6000	−0.2000	−0.4000	0.3333	1.0000										
Mes17	−0.6667	−0.6667	−0.3333	−0.3333	0.0000	0.6000	1.0000									
Mes18	−0.3333	−0.3333	0.3333	0.3333	0.6000	0.6000	0.4000	1.0000								
Srisk15	.	.	.	.	.	0.6667	.	1.0000	1.0000							
Srisk16	.	.	.	.	.	0.3333	.	0.3333	−0.3333	1.0000						
Srisk17	.	.	.	.	.	.	.	.	.	.	1.0000					
Srisk18	.	.	.	.	.	1.0000	.	1.0000	0.0000	0.6667	.	1.0000				
Bsl15	0.3333	0.3333	0.0000	0.0000	0.4667	−0.6667	−0.3333	0.4000	.	.	.	.	1.0000			
Bsl16	0.3333	0.3333	0.0000	0.0000	0.4667	−0.6000	−0.8000	0.0667	0.3333	−0.3333	.	0.3333	0.9444	1.0000		
Bsl17	0.3333	0.3333	0.0000	0.0000	0.4667	−0.6000	−0.8000	0.2000	0.3333	−0.3333	.	0.3333	0.8889	0.8667	1.0000	
Bsl18	0.3333	0.3333	0.0000	0.0000	0.4667	−0.6000	−0.8000	0.2000	0.3333	−0.3333	.	0.3333	0.8889	0.8667	1.0000	1.0000

A. Robustness Test

1. Impute three-month T-bill data

. summm

Variable	Obs	Mean	Std. Dev.	Min	Max
Date	2,971	19749.43	1269.313	17533	21913
MOLIBOR	2,971	1.024651	.9536291	.22285	4.81875
MOTBILL	2,302	6.084313	1.474008	3.721	11.55471
YRTBOND	2,971	8.188854	2.028928	5.047	20.955
INDOJIBON	2,971	5.608955	1.373478	3.20861	11.97222
JIBOR1W	2,971	5.944626	1.349811	3.8044	10.50028
JIBOR1MO	2,971	6.590463	1.443273	3.9716	11.79167
JIBOR3MO	2,971	6.986121	1.470088	4.19	12.59722
JIBOR6MO	2,971	7.291413	1.503186	4.4196	13.44444
JIBOR12MO	2,971	7.53949	1.530414	4.82	14.25

. mi misstable summarise, all

Variable	Obs=.	Obs>.	Obs<.	Obs<. Unique values	Obs<. Min	Obs<. Max
Date			2,971	>500	17533	21913
MOLIBOR			2,971	>500	.22285	4.81875
MOTBILL	669		2,302	>500	3.721	11.55471
YRTBOND			2,971	>500	5.047	20.955
INDOJIBON			2,971	>500	3.20861	11.97222
JIBOR1W			2,971	>500	3.8044	10.50028
JIBOR1MO			2,971	>500	3.9716	11.79167
JIBOR3MO			2,971	>500	4.19	12.59722
JIBOR6MO			2,971	>500	4.4196	13.44444
JIBOR12MO			2,971	>500	4.82	14.25

. mi impute regress MOTBILL JIBOR1W JIBOR1MO JIBOR3MO JIBOR6MO, add(660) rseed(1234)

```
Univariate imputation                       Imputations =       660
Linear regression                                 added =       660
Imputed: m=1 through m=660                      updated =         0
```

Variable	Observations per m: Complete	Incomplete	Imputed	Total
MOTBILL	2302	669	669	2971

(complete + incomplete = total; imputed is the minimum across m
of the number of filled-in observations.)

2. Spearman's Rho correlation

	CoVaR15	CoVaR16	CoVaR17	CoVaR18	Mes15	Mes16	Mes17	Mes18	Srisk15	Srisk16	Srisk17	Srisk18	Bsl15	Bsl16	Bsl17	Bsl18
CoVaR15	1.0000															
CoVaR16	-0.0857	1.0000														
CoVaR17	0.7714	-0.2000	1.0000													
CoVaR18	0.8286	0.0857	0.9429	1.0000												
Mes15	-1.0000	-1.0000	-0.8000	-0.8000	1.0000											
Mes16	-0.6000	-0.7000	-0.2000	-0.6000	0.4000	1.0000										
Mes17	-0.8000	-0.8000	-0.6000	-0.6000	-0.1000	0.8000	1.0000									
Mes18	-0.5000	-0.5000	-0.6000	0.5000	0.7000	0.6571	0.5000	1.0000								
Srisk15	-1.0000	-1.0000	0.5000	-1.0000	0.0000	0.8000	1.0000	1.0000	1.0000							
Srisk16	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	1.0000	0.5000	-0.4000	1.0000						
Srisk17	0.0000	0.0000	0.0000	0.0000	0.0000	-1.0000	-1.0000	-1.0000	-1.0000	-1.000	1.0000					
Srisk18	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	1.0000	1.0000	-0.2000	0.8000	-1.0000	1.0000				
Bsl15	0.4000	0.4000	0.0000	0.0000	0.6000	-0.8000	-0.3714	0.5000	-1.0000	1.0000	0.0000	1.0000	1.0000			
Bsl16	0.4000	0.4000	0.0000	0.0000	0.6000	-0.7000	-0.9000	0.0286	0.5000	-0.5000	0.0000	0.5000	0.9833	1.0000		
Bsl17	0.4000	0.4000	0.0000	0.0000	0.6000	-0.7000	-0.9000	0.2571	0.5000	-0.5000	0.0000	0.5000	0.9500	0.9515	1.0000	
Bsl18	0.4000	0.4000	0.0000	0.0000	0.6000	-0.7000	-0.9000	0.2571	0.5000	-0.5000	0.0000	0.5000	0.9500	0.9515	1.0000	1.0000

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Chapter 5: Co-movement and Interconnectedness: Network Model Application of Systemic Risk

This chapter explore how capital market data and asset returns could be a good proxy for detecting interconnectedness and risk mapping in the financial system. Our sample employs a mixture of stock market and prudential data from Indonesian banks from 2012-2019 period. The principal component analysis and Granger causality showed that the core banks in the network could explain the variance, risk commonality, and shocks propagation. Moreover, our results aligned with Basel calculations to score the interconnectedness. The dominance of big banks in the centrality measures also raises the issue of substitutability. This chapter outstretched theories to provide a basis for policy makers to develop supervision frameworks to impede systemic risk.

5.1 Introduction

Intercorrelated exposure is a common operational activity carried out by financial institutions. Banks, as the key financial institutions in most countries, have intra-financial assets and liabilities to source liquidity needs and to invest excess funds in other institutions. Under normal economic conditions, the transactions follow the supply and demand mechanism of a competitive financial market. A problem arises when disruptions arise either from unsystematic internal failures such as fraud or external shocks such as the Asian financial crises in 1997 and the global financial crises of 2007–2008.

Theoretically, the interactions among financial products create a complex network that could trigger systemic failure through interconnectedness. The failure of one important bank in the network could arise from trading activities, poor risk management, moral hazards or fraud, which might trigger financial distress to its counterpart. The insolvency condition might then by amplified throughout the system if the capital buffer of distress bank below its losses. Intercorrelated exposures within the banking system and their impact on the economy provide the basis for policy makers and scholars to develop network models of systemic risk. Basel's first guideline for identifying systemic banks was issued in November 2011; it was then further updated, with its latest amendment being integrated in 2018 (BCBS 2011, 2018).

The use of network model applications to study systemic risk has gained popularity, as it allows researchers to highlight market infrastructure oversights using different data and statistical methods. The importance of studying systemic risk using network models has also gained attention and has been highlighted by the European Central Bank, which discussed the advanced methods employed in network analysis (ECB 2009b). Our goal is to conduct research that incorporates the theoretical and practical application of systemic risk in the banking system.

The exploration of the correlated exposure within the network of financial institutions started long before the 2007–2008 global financial crises. Seminal papers by Allen and Gale (2000) discuss the possibility of contagion and explain how the incompleteness of a risk allocation structure within the system could cause systemic failure. Eisenberg and Noe (2001) modelled cyclical interdependence using a mechanism that shows how multidimensional clearing vectors exist and depend on several aspects. Another strand of systemic risk research imposed on network models, such as the work of Gai and Kapadia (2010), exhibits how financial systems feature a robust but fragile tendency by which the probability of systemic failure might be low, but the impact could be severe. Other researchers, such as Krause and Giansante (2012); Elsinger, Lehar and Summer (2006a); Billio et al. (2012) and Chan-Lau (2010), applied network models.

Other researchers, including Cont et al. (2013), Chan-Lau (2010), Fang et al. (2018) and Das (2016), have also applied network model used for emerging economy evidence. However, systemic risk studies using Indonesia banking data are quite limited. The vast majority of papers have used cross-sectional measures. For instance, Salim and Daly (2021) used CoVaR, MES and SRISK; Koesrindartoto and Aini (2020) employed VaR, MESh, MESdcc and LRMES; Raz (2018) utilised Z-score and Delta-CoVaR and Hermanto and Ayomi (2014) used CoVaR. Meanwhile, Muhajir et al. (2020) employed the copula approach, while Wibowo (2017) used distance to default.

Although a number of papers have discussed systemic risk using network models, none of the above manuscripts empirically investigated systemic banks using a network model or Basel indicator-based method simultaneously. Several reasons for this can be tracked to research constraints and technical issues regarding access to and the compilation of restricted prudential data. Our research fills the gap by gauging systemic banks based on market data and comparing these data with Basel interconnectedness results built on microprudential bank data. This study is also a pioneer study in estimating systemic risk utilising a network model approach in the Indonesia banking context. This research uses Indonesian datasets because of the growing importance of this country among the emerging economies in Asia as a member of G-20 countries. The Indonesian banking system is appealing to explore, as it contains more than 110 registered commercial banks that vary in size. Owing to this situation, network model analysis could provide valuable insights into systemic risk investigation in Indonesia.

Three research questions are posed in this chapter: i) Could capital market data and assets returns indicate increased risk and the direction of risk? ii) Which banks are dominant and could potentially trigger systemic risk in the Indonesia banking network? iii) How do the network approach conclusions compare to the Basel interconnectedness outcome? To answer the research questions, we use empirical approaches following Billio et al. (2012). That is, we use principal component analysis (PCA) to measure the institution's risk commonality returns and risk direction. We also use Granger causality to examine the SIBs within the banking network. In the last part of our analysis, we compute the systemic bank to compare Basel interconnectedness score results with the results derived using the former method.

The outcomes of this research will help enhance the general understanding of systemic risk study, particularly regarding risk co-movement and interconnectedness, systemic banks within banking networks and the comparison of the results with eh results derived from the Basel-based method. The results are also beneficial for bank supervisors concerning assessing the overall risk of the financial system and identifying the important bank in the overall financial system.

The main findings of our research are as follows. First, stock market data can be used as a proxy to identify returns' co-movements, which indicate the interconnectedness. Second, the PCA method results exhibit that the first three principal components seize a significant portion of the variance. This method envisages the increase of risk commonality and interconnection in the financial system. Third, the Granger centrality measure shows that the core banks in the Indonesian banking network are predominantly large banks. This outcome raises the issue of substitutability. Fourth, the supremacy of KBMI 4 and KBMI 3 banks also inline vis-à-vis the Basel indicator-based method that involves prudential data as employed by policy makers.

This chapter is structured as follows: Section 2 presents the literature review and highlights the importance of the network model approach in studying systemic risk. Section 3 contains the data details and the methodology framework used. Section 4 provides the analytical results and interpretation, and Section 5 offers conclusions and policy recommendations.

5.2 Literature Review

5.2.1 Theoretical Approaches

Policy makers, the FSB, IMF and BIS (2009) define systemic risk as the risk of disruption to financial services that impair all or parts of a financial system and could have serious negative consequences for the real economy. The European Central Bank (2009a) defines systemic risk as the risk of financial instability that impairs the functioning of a financial system by which economic growth and welfare suffer significantly. Bank Indonesia (2014), as the macro-prudential regulator of Indonesia's banks, defines systemic risk as the potential for system-wide instability in the financial sector as the result of exaggerating procyclicality actions taken by financial institutions. However, no uniform systemic risk definition reflects the complexity of factors surrounding systemic risk study. Nevertheless, the catastrophic effect of systemic failure is clear.

The economic cost of the latest 2008 banking crisis was catastrophic and raised critiques from society regarding the amount of bailout required and the further impact on the economy. The output losses associated with the crisis range from several trillion to over $10 trillion. Research by Boyd, Kwak and Smith (2005) indicates that the more persistent effects of crises prior to 2007 indicate that output losses reached more than 100% of pre-crises GDP. The financial crises also impacted unemployment, household wealth and the number of foreclosures. The BCBS (2010) reported the costs of banking crises by comparing the shift in the GDP trend after the crises compared to the pre-crises GDP trend. The cumulative losses of the crises could have been greater if the losses were estimated in the long run.

De Bandt and Hartmann (2000) defined systemic risk as a systemic event that strongly affects many financial institutions or markets, thereby severely impairing the general functioning of the financial system. Some approaches follow the definitions of research variables like intercorrelated exposures (Acharya et al. 2017), which are a set of circumstances that threatens the stability of public confidence in the financial system (Billio et al. (2012). Regulators and researchers should consider various indicators in the near future to assess the complexity of systemic risk (Bengtsson, Holmberg & Jonsson 2013).

Taxonomy research on SIBs and systemic risk have been classified based on the statistics estimation, variables, methodologies and intercorrelated interactions known as a network model. Bisias et al. (2012) classified the study using a supervisory scope, research methodology and data employed in the manuscripts. The authors offered definitions for the risks measurement to include required inputs, expected outputs and data conditions. Nevertheless, based on the same paper, the direction of systemic risk papers could be classified into five major categories.

The first is the probability distribution using cross-section data. For example, Adrian and Brunnermeier (2016) proposed CoVaR to calculate the VaR of banks and its risk effect on other banks when the financial system is under stress. Other researchers (Acharya, Engle & Richardson 2012; Acharya 2009; Acharya et al. 2017) introduced marginal and systemic expected shortfall (MES-SES) to measure financial institutions' expected losses when the market falls below a predefined threshold over a specific time horizon. In other work, Brownlees and Engle (2017) introduced systemic risk measure (SRISK) to calculate the expected capital shortage of a firm given its leverage and MES (i.e. the expected loss an equity investor in a financial firm would experience if the overall market declined substantially).

The second is contingent claims and default and liquidity, by which the probability of default of each institution and their link to financial system-wide through joint distribution can be estimated. Examples of papers in this category were produced by Jobst and Gray (2013) and Jobst (2014).

The third is the network analysis method measures the connectedness between banks and their failure impacts on other banks and the overall financial system. Studies in this category have been conducted by Allen and Gale (2000); Eisenberg and Noe (2001); Gai and Kapadia (2010) and Gai, Haldane and Kapadia (2011).

Studies of the fourth category use extreme value theory (EVT) to investigate the contagion risk. Examples of such studies include those conducted by Rocco (2014), Dias (2014), Akhter and Daly (2017) and Daly et al. (2019).

Systemic risk studies have been done in emerging economies such as Roengpitya and Rungcharoenkitkul (2011) using Thailand's banking system data and found that large banks contribute more to systemic risk than small banks. However, bank size is not the dominant factor. Using monthly banking supervision data, the researchers applied the concept of CoVaR, as introduced by Adrian and Brunnermeier (2016), to measure the financial linkages and revealed that financially linked institutions have the greatest effect on systemic risk in the banking system.

In other research, Cont et al. (2013) applied mutual exposures and capital level when examining Brazilian banks. They found that the interbank network exhibits a complex heterogeneous structure concentrated on a few nodes. Balance sheet size alone is not a strong indicator of systemic importance, and thus, the researchers proposed using the contagion index. Chan-Lau (2010) examined a balance sheet-based network from direct exposures in Chile. They suggested that financial surveillance is better when focused on domestic banks' links with foreign banks and non-bank financial institutions.

Fang et al. (2018) used datasets from Chinese banks to compare five popular systemic risk banking. They combined the systemic risk measure based on principal component analysis to provide reliable rankings. In another study, Das (2016) considered the Indian banking sector using a systemic risk approach based on the level of node vulnerability. They developed a system-wide score with a new aggregate score, normalised, fragility. This score also considers the risk of decomposition and spillover.

Studies on banking systemic risk in Indonesia are quite limited. A recent paper by Salim and Daly (2021) modelled Indonesian systemic banks using CoVaR, MES and SRISK. They exhibited the intertheoretical model correlation and approximated its ranking results in concordance with the Basel indicator-based methodology as applied by policy makers. In other work, Koesrindartoto and Aini (2020) regressed bank characteristics to systemic risk using VaR, MESh, MESdcc and LRMES, while Muhajir et al. (2020) developed a joint default probability index using the copula approach. Wibowo (2017) used Merton's distance to default to measure the effects of bank capital buffer and leverage on systemic risk. Raz (2018) employed Z-score and Delta-CoVaR to estimate the idiosyncratic and systemic risk, and Hermanto and Ayomi (2014) applied the Merton model to determine the probability of default for over 30 banks in Indonesia from 2002–2013.

5.2.2 Network Model Methods

Systemic risk research based on network theory gained popularity for modelling financial institutions' failure long before the financial crises that occurred from 2007–2008. For instance, in their seminal paper on systemic risk, Allen and Gale (2000) showed how the market structure could affect the impact of systemic risk. They found that a complete structure of proof is more robust than an incomplete one. In other research, Eisenberg and Noe (2001) modelled cyclical interdependence using a mechanism showing how multidimensional clearing vectors exist and depend on several factors. Meanwhile, Gai and Kapadia (2010) exhibited that financial systems feature a robust yet fragile tendency by which the probability of systemic failure could be low while the impact could be severe.

Similar strands of research include the study conducted by Cont, Moussa and Santos (2013). They analysed individual Brazilian banks' balance sheets and network structures from 2007–2008 and identified failed banks' contributions to systemic risk. Using a metric for the systemic importance of institutions (called the contagion index), they measured the expected losses suffered by the network triggered by the default of an institution in a macroeconomic stress scenario. Later, Krause and Giansante (2012) developed a model for assessing interbank loans given and received by banks of different sizes. The results indicated that the size of the failing bank has a limited impact on the number of banks affected by contagion and concluded that the bank's network structure has a much more significant impact on systemic risk.

This method was also utilised by Elsinger, Lehar and Summer (2006a) in the extended model used by Eisenberg and Noe (2001) to include uncertainty to quantify the correlated exposure and domino effect. Furthermore, Elsinger, Lehar and Summer (2006b) analysed the network analysis correlated exposure and mutual credit relation that may cause a domino effect.

5.2.3 Basel Indicator-Based Guideline

The first guideline for identifying systemic banks was issued by Basel in 2011 in response to the global financial crises that occurred in 2007 and 2008 (BCBS 2011). The background to these events was a harmful failure effect of large institutions, which transmitted shocks across borders. The negative externalities encompassed economic crises, corporate bankruptcies, GDP losses and unemployment (BCBS 2012). The Basel G-SIBs guidelines are used to evaluate banks into five categories based on 13 indicators: cross-jurisdictional activity, size, interconnectedness, substitutability and complexity. It is relatively easy to calculate a bank’s score, as the weight proportion is equally divided into 12 indicators from the data compiled at the micro level or bank balance sheet data.

Basel provides room for the discretion of local bank authorities to adjust indicators to better capture domestic banks’ characteristics based on specific factors in the local economy (BCBS 2012). For our dataset, we adjust the formulae composition and re-arrange the indicators following POJK No. 2/POJK.03/2018 (OJK 2018). OJK, as the banking supervisor, simplified the Basel guideline into three categories (size, interconnectedness and complexity) based on eight equally weighted indicators. The newest Basel guidelines introduced a trading volume indicator, changes in percentage weights for substitutability and an extension to represent insurance subsidiaries (BCBS 2018).

Although many studies have investigated systemic risk, no study has empirically investigated systemic banks using the network model and a methodology based on the Basel guidelines. This could be because of the research scope of such a study and restricted access to bank balance sheet prudential data. Our manuscript fills this gap by employing PCA and Granger causality (Billio et al. 2012) to assess systemic banks based on market data and comparing the outcomes derived from this method with Basel interconnectedness results based on microprudential bank data (BCBS 2018). This study can also be considered a pioneering work since it estimates systemic risk by utilising a network model approach in the Indonesian banking context. The results will help bank supervisors monitor the escalation of risk and predict how it might spread, thereby impeding systemic risk.

5.3 Data and Methodology

5.3.1 Sources of Data

We examined all commercial banks listed on the Indonesia Stock Exchange from 2012–2019. The initial sample comprised 33 banks, which was subsequently reduced to 27 banks because of inactive trading or missing data. The shares prices, outstanding shares, JSX index and market capitalisation of Indonesian banks are recorded at a daily frequency. For the total assets and total equity, the data are quarterly. All market data are sourced from Eikon Thomson Reuters databases.

In addition, for the Basel interconnectedness calculation, we gather the monthly balance sheet reports submitted to OJK, which encompasses all 115–120 Indonesian commercial banks. The number of banks varies because of mergers, acquisitions and revoked licenses during the study period. For each category of the Basel method, we also need details of the data accounts (e.g., intra-financial assets, intra-financial liabilities and securities outstanding). Moreover, the structure of the data requires us to compile a second tier of balance sheet details (i.e., secured debt, senior unsecured debt, subordinated debt and equity market capitalisation). To compare PCA and Granger causality results with the Basel method results, we tick it to 2016–2018. The time frame was chosen in line with the Indonesian SIBs' regulations issued by OJK (2015); it is more current and improves the information made available to the regulator.

5.3.2 Model Estimation

The model described in this chapter uses three methods to answer the research questions. First, we adopt principal component analysis (PCA) to measure the interconnectedness of the asset returns of Indonesian banks. PCA offers the advantage of reducing data dimension, increasing interpretability, and minimising information loss (Jolliffe & Cadima 2016). PCA could also detect the downside risk of large financial institutions' failures (Baek, Cursio & Cha 2015; Billio et al. 2012).

Second, we employ Granger causality to evaluate the risk spread direction among banks considering several network indicators: degree of causality, number of connections, closeness and eigenvector centrality. Granger causalities fill the need of systemic risk scholars to map institutions that could trigger systemic risk within the financial network (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020; Zheng & Song 2018). For the PCA and Granger causality, we follow Billio et al. (2012).

Third, follow the Basel indicator-based methodology to calculate the systemic risk rankings in the Indonesian banking environment. Basel standards are the guidelines for the BIS member countries, including Indonesia, and adopting these standards shapes the comparability and is widely acknowledged for prudential regulations.

5.3.2.1 Principal Component Analysis

The use of high-frequency data and PCA as an adaptive descriptive statistic is applied in many research fields. The implementation of PCA has been used to analyse systemic risk by Billio et al. (2012); Fang et al. (2018) and Baek, Cursio and Cha (2015). We conform to the method of Billio et al. (2012) for measuring the degree of interconnectedness asset returns of financial institutions into orthogonal factors of decreasing explanatory power.

R^i = stock return of institutions i, $i=1,....,N$, system aggregate return $R^s = \sum_i R^i$,

$E[R^i] = \mu_i$ and $Var[R^i] = \sigma_i^2$ to have

$$\sigma_s^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_i \sigma_j \, E\left[z_i \, z_j\right]$$

$$Z_k \equiv \frac{(R^k - \mu_k)}{\sigma_k} \quad k = i,j$$

where z_k is the standardised return of institutions k and σ_s^2 is the variance of the system. If we put λ_k the k-th eigenvalue with N zero mean uncorrelated variables

$$\mathrm{E}\,[\zeta_k \zeta_l] = \begin{cases} \lambda_k & if\ k = 1 \\ 0 & if\ k = 0 \end{cases}$$

$$Z_i = \sum_{k=1}^{N} L_{ik} \, \zeta_k$$

where L_{ik} is a factor loading for ζ_k for an institution i. Then we have

$$\mathrm{E}\left[Z_i Z_j\right] = \sum_{k=1}^{N} \sum_{l=1}^{N} L_{ik} L_{jl} \, \mathrm{E}\,[\zeta_k \zeta_l] = \sum_{k=1}^{N} L_{ik} L_{jk} \lambda_k$$

$$\sigma_s^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k$$

focus on subset n < N, where this set seizes most of the volatility during crises and indicates the increased interconnectedness among banks. If the total risk of the system is defined as $\Omega \equiv \sum_{k=1}^{N} \lambda_k$ and $\omega_n \equiv \sum_{k=1}^{N} \lambda_k$ the risk associated with the first principal components is $\frac{\omega_n}{\Omega} \equiv h_n \geq H$. The contribution of $\mathrm{PCA}_{i,n}$ of institution i to the risk of the system is calculated as

$$PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_s^2} \frac{\vartheta \sigma_s^2}{\vartheta \sigma_i^2} \mid h_n > H$$

$$PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_s^2} \frac{\vartheta \sigma_s^2}{\vartheta \sigma_i^2} \mid h_n \geq H = \sum_{k=1}^{N} \frac{\sigma_i^2}{\sigma_s^2} L_{ik}^2 \, \lambda_k \mid h_n \geq H$$

5.3.2.2 Granger Causality

The linkage of the network model approach with the Granger causality builds on its ability to predict values based on information from other previous time series. In the capital market, which involves friction, the Granger causality appears in the assets return based on other institutions' returns, indicating the spillover risk (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020; Zheng & Song 2018). We use Granger causality to evaluate the direction of risk spreading in the financial system during crises. Refer to Billio et al. (2012) for a complete description of the formula.

$$(j \rightarrow i) = \begin{cases} 1 & \text{if j Granger causes i} \\ 0 & \text{otherwise} \end{cases}$$

The interconnectedness measures consist of:

a. *Degree of Granger causality* (DGC), which measures the association of N(N-1) pairs of N banks:

$$DGC \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq 1} (j \rightarrow i)$$

b. *Number of connections,* which captures the importance of banks during the systemic event:

$\#Out$: $(j \rightarrow S)|DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} (j \rightarrow i)|DGC \geq K'$

$\#In$: $(S \rightarrow j)|DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} (i \rightarrow j)|DGC \geq K'$

$\#In + Out$: $(j \leftrightarrow S)|DGC \geq K = \frac{1}{2(N-1)} \sum_{i \neq j}^{N} (i \rightarrow j) + (j \rightarrow i)|DGC \geq K'$

where *S*: system, *#Out*: number of banks Granger-caused by institution *j,* and *#In*: number of banks Granger-cause institution *j*, and *#In+Out*: the sum.

c. *Sector-conditional connections*, which is used to determine which types of banks KBMI affect the other classes:

$\#Out - to - Other$: $\frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left((j|\alpha) \rightarrow (i|\beta)\right)|DGC \geq K'$

$\#In - from - Other$: $\frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left((i|\beta) \rightarrow (j|\alpha)\right)|DGC \geq K'$

$\#In + Out - Other$: $\frac{\sum \beta \neq \alpha \sum i \neq j \left((i|\beta) \rightarrow (j|\alpha)\right) + \left((j|\alpha) \rightarrow (i|\beta)\right) |DGC \geq K'}{2(M-1)N/M}$

where *M*: banks KBMI 1 - 4, *#Out-to-Other*: number of banks KBMI Granger-caused by institution *j,* and *#In-from-Other*: number of banks KBMI Granger-cause institution *j* and *#In+Out-Other*: the sum of two.

d. *Closeness*, which is used to estimate the shortest edges between financial institutions and is defined as

$$C_{jS}|_{DGC \geq K} = \frac{1}{N-1} \sum_{i \neq j} C_{ji} \left(j \xrightarrow{C} i\right) |DGC \geq K'$$

e. *Eigenvector centrality*, which is the signal of bank significance within the network based on their connection to other banks

$$V_j|_{DGC\geq K} = \sum_{i=1}^{N} [A]_{ji} V_i|_{DGC\geq K\prime}$$

5.3.2.3 Basel Indicator-Based Approach

The BCBS (2018) indicator-based approach is used to evaluate the institution size, interconnectedness, substitutability, global cross-jurisdictional activity and complexity. This approach allows for departures from the BCBS (2012) guidelines to better capture specific D-SIBs' characters and country externalities. For our dataset, we adjust the formulae composition and re-arrange the indicators following POJK No. 2/POJK.03/2018. The SIBs assessment indicators (after country adjustment) are listed in Table 5.1 below.

Table 5.1. Indonesia D-SIBs Method

Category and weighting	BCBS G-SIBs	Indicator weighting	Category (weighting)	Adjusted Indicators D-SIBs	Indicator weighting
Size (20%)	Total exposures	20%	Size (33.3%)	Total exposures	100%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Interconnectedness (33.3%)	Intra-financial system assets	33.3%
	Intra-financial system liabilities	6.67%		Intra-financial system liabilities	33.3%
	Securities outstanding	6.67%		Securities outstanding	33.3%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	Complexity (33.3%)	Notional amount of over-the-counter (OTC) derivatives	25%
	Level 3 assets	6.67%		Trading and available-for-sale securities	25%
	Trading and available for sale securities	6.67%		Domestic indicators	25%
				Substitutability (payment system & custodian)	25%
Substitutability (20%)	Assets under custody	6.67%			
	Payment activity	6.67%			
	Underwritten transactions in debt & equity markets	3.33%			
	Trading volume	3.33%			
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%			
	Cross-jurisdictional liabilities	10%			

Source: OJK (2018).

To calculate the score value for a given indicator, we follow BCBS (2014). Specifically, we divide the bank's value by the total value of the banking system and present the results in basis points (bps).

$$\frac{Bank\ indicator}{Sample\ total} \text{ x } 10{,}000 = \text{Indicator score (bps)}$$

When generating the Basel network map, we focus on the interconnectedness score category only. This score is the average of intra-financial assets, intra-financial liabilities, and securities outstanding.

5.4 Results

5.4.1 Statistics Summary

The datasets are classified following OJK (2016a); specifically, the banks are grouped into four classes of KBMI based on their core capital. A bank's class determines its business network and activities, with the most complex activities licensed for banks classified in KBMI 4; meanwhile, KBMI 1 banks are permitted only to offer basic banking services. The Excel worksheet includes shares price, market capitalisation, total assets, total equity, and sample groups. Share prices, market capitalisation, JSX LQ45 excess return and JSX financial sector excess return are provided daily. Other data, such as total assets and total equity, provided quarterly. The sample banks are listed in Table 5.2 below.

Table 5.2. Sample Banks

No.	Ticker	Bank	KBMI
1	BCA	PT. Bank Central Asia Tbk.	4
2	BRI	PT. Bank Rakyat Indonesia (Persero) Tbk.	4
3	BMRI	PT. Bank Mandiri (Persero) Tbk.	4
4	BNI	PT. Bank Negara Indonesia (Persero) Tbk.	4
5	MEGA	PT. Bank Mega Tbk.	3
6	MAYA	PT. Bank Mayapada Internasional Tbk.	2
7	BNLI	PT. Bank Permata Tbk.	3
8	BDMN	PT. Bank Danamon Indonesia Tbk.	3
9	PNBN	PT. Bank Pan Indonesia Tbk.	3
10	NISP	PT. Bank OCBC NISP Tbk.	3
11	BNGA	PT. Bank CIMB Niaga Tbk.	3
12	BTPN	PT. Bank BTPN Tbk.	3
13	MAYBANK	PT. Bank Maybank Indonesia Tbk.	3
14	BJBR	PT. Bank Pembangunan Daerah Jawa Barat Tbk.	2
15	BTN	PT. Bank Tabungan Negara (Persero) Tbk.	3
16	BSIM	PT. Bank Sinarmas Tbk.	1
17	BJTM	PT. Bank Pembangunan Daerah Jawa Timur Tbk.	2
18	SDRA	PT. Bank Woori Saudara Indonesia Tbk.	2
19	BACA	PT. Bank Capital Indonesia Tbk.	1
20	AGRO	PT. BRI Agroniaga Tbk.	1
21	CCBI	PT. Bank China Construction Indonesia Tbk.	1
22	BBKP	PT. Bank Bukopin Tbk.	2
23	MNC	PT. Bank MNC Internasional Tbk.	1
24	QNB	PT. Bank QNB Indonesia Tbk.	1
25	BAG	PT. Bank Artha Graha Internasional Tbk.	1
26	BNBA	PT. Bank Bumi Arta Tbk.	1
27	BVIC	PT. Bank Victoria Internasional Tbk.	1

In total, there are 1,864 daily observations for each variable from 2012–2019. To estimate the PCA and Granger causality, we use Belluzo's (2020) Matlab code for systemic risk. Based on the analysis of mean daily returns (shown in Table 5.3.), MAYA and BBNI confer the most, with 0.18% and 0.14%, followed by MEGA, BACA and CCBI, with 0.1%. The results showcase that the most profitable banking shares returns from 2012–2019 if an investor invested their money by buying MAYA and BBNI shares. The BBNI return distribution curve is positively skewed and left-leaning from the mean. During the same period, investors suffer losses if they invest their money in the BBKP, MNC, Maybank and BAG, with losses estimated at -0.03%, -0.02% and -0.01%, respectively. Though BBNI offered one of the highest paybacks, its deviation was also the highest (4.59%), followed by MAYA (4.53%). The returns for all samples are summarised in Table 5.3.

Table 5.3. Summary Statistics Daily Returns

Variable	Mean	Std. Dev.	Min	Max	Skew	Kurtosis
BCA	0.09%	1.45%	-7.89%	7.95%	0.11	6.92
BRI	0.08%	1.93%	-8.33%	11.81%	0.15	6.20
BMRI	0.06%	1.92%	-7.83%	13.67%	0.34	6.46
BNI	0.14%	4.59%	-7.98%	180.75%	32.73	1,288.47
MEGA	0.10%	2.74%	-17.65%	25.00%	1.57	21.00
MAYA	0.18%	4.53%	-25.00%	25.00%	0.97	13.73
BNLI	0.03%	2.46%	-12.32%	24.73%	2.08	20.73
BDMN	0.01%	2.42%	-19.77%	19.06%	0.25	12.50
PNBN	0.06%	2.43%	-10.53%	16.18%	0.77	7.19
NISP	0.08%	3.63%	-50.00%	99.05%	10.02	321.80
BNGA	0.01%	2.11%	-12.03%	24.44%	1.57	18.93
BTPN	0.01%	1.91%	-9.82%	24.90%	2.24	25.26
Maybank	-0.01%	2.23%	-7.85%	34.34%	5.00	64.14
BJBR	0.04%	2.50%	-10.09%	22.92%	1.73	15.47
BTN	0.05%	2.30%	-15.03%	11.11%	0.11	6.02
BSIM	0.08%	2.81%	-23.43%	25.00%	1.10	23.07
BJTM	0.04%	1.82%	-9.30%	15.74%	0.69	11.26
SDRA	0.09%	3.51%	-24.54%	25.00%	0.49	19.46
BACA	0.10%	2.73%	-13.79%	34.71%	2.30	26.17
AGRO	0.08%	3.38%	-12.74%	34.51%	3.59	28.81
CCBI	0.10%	4.32%	-40.42%	67.84%	3.82	53.97
BBKP	-0.03%	2.04%	-16.74%	24.86%	1.12	22.00
MNC	-0.02%	2.47%	-14.66%	21.54%	1.70	16.96
QNB	0.07%	4.50%	-25.00%	32.35%	0.12	14.54
BAG	-0.01%	2.24%	-14.39%	34.34%	4.54	68.52
BNBA	0.05%	2.10%	-13.69%	14.07%	0.30	10.97
BVIC	0.02%	3.03%	-19.39%	34.85%	2.51	31.14

Moreover, the return correlation discloses that BRI and BMRI have the strongest association (65.89%), followed by BMRI-BCA (49.89%) and BRI-BCA (49.79%), respectively. We can interpret this as an indicator of co-movement across the banking shares and the exposures of interconnectedness in banking activities. Other strong interrelations were found for BTN – BCA, BJTM – BJBR, BDMN – BRI, BDMN – BMRI and BNI – BRI as can be seen in Table 5.4. The correlations are dominated by banks in the KBMI 4 and KBMI 3 categories.

Table 5.4. Returns Correlation

	BCA	BRI	BMRI	BNI	MEGA	MAYA	BNLI	BDMN	PNBN	NISP	BNGA	BTPN	Maybank	BJBR	BTN	BSIM	BJTM
BCA	1																
BRI	0.4979	1															
BMRI	0.4989	0.6589	1														
BNI	0.2032	0.2799	0.2774	1													
MEGA	0.0138	0.0065	0.0015	0.011	1												
MAYA	0.0352	0.0503	0.0478	-0.0115	-0.028	1											
BNLI	0.0976	0.1087	0.0941	0.0392	-0.0058	0.0157	1										
BDMN	0.246	0.2989	0.2903	0.1211	0.0311	0.0295	0.0706	1									
PNBN	0.1966	0.2481	0.2582	0.1081	0.006	0.023	0.1426	0.0963	1								
NISP	0.014	-0.0289	0.0388	0.0117	0.046	0.0227	0.0188	-0.0036	-0.0158	1							
BNGA	0.1842	0.22	0.2555	0.0978	-0.0132	-0.001	0.1207	0.1361	0.155	-0.0037	1						
BTPN	0.148	0.12	0.1534	0.0657	-0.0117	0.0427	0.0573	0.0867	0.1091	-0.0226	0.0817	1					
Maybank	0.0756	0.1141	0.1304	0.032	-0.022	0.029	0.1375	0.1069	0.1029	0.0397	0.2247	0.0416	1				
BJBR	0.1964	0.2246	0.2496	0.0573	0.0052	0.0304	0.0433	0.1225	0.1244	-0.0046	0.0963	0.0548	0.0912	1			
BTN	0.3342	0.457	0.456	0.1831	0.0012	0.0425	0.096	0.1637	0.2321	0.0535	0.2341	0.1165	0.1324	0.2544	1		
BSIM	0.022	0.0205	0.0312	0.0055	0.0213	-0.0001	0.0052	0.0249	0.037	-0.0009	0.0722	0.0222	0.0189	0.0149	0.0277	1	
BJTM	0.1974	0.2405	0.2515	0.1141	-0.002	0.0037	0.0791	0.1147	0.1712	0.0346	0.1691	0.1035	0.1377	0.2999	0.2348	0.0164	1
SDRA	0.0092	0.0036	0.0041	0.0126	0.0072	0.0336	0.0207	-0.0093	-0.0114	0.0274	-0.0014	0.0392	-0.0086	-0.0091	-0.0084	0.0114	0.0159
BACA	0.0488	0.0749	0.0931	0.0676	0.0069	-0.0307	0.0373	0.0373	0.0708	0.0335	0.0239	-0.0045	0.0016	0.0324	0.0684	0.0108	0.0204
AGRO	0.1099	0.1432	0.1724	0.0735	0.0028	0.0414	0.1205	0.0488	0.0983	0.0219	0.0985	0.0858	0.2163	0.0659	0.1401	0.0255	0.1149
CCBI	0.0708	0.0947	0.1048	0.0401	-0.0087	0.013	0.047	0.0464	0.0318	0.012	0.1072	0.025	0.0995	0.0348	0.0699	0.0137	0.0442
BBKP	0.2214	0.2674	0.27	0.1027	0.0104	-0.0038	0.1062	0.1237	0.1693	-0.0146	0.1917	0.0626	0.1773	0.1644	0.207	0.0252	0.1725
MNC	0.1211	0.1406	0.1566	0.0549	0.0267	-0.0027	0.0284	0.0797	0.0921	-0.0233	0.0519	0.0555	0.1284	0.0892	0.113	-0.004	0.0985
QNB	-0.0478	-0.0166	-0.0173	-0.0031	-0.0349	0.0273	0.0519	0.0129	-0.0038	0.0626	-0.0173	-0.0133	-0.0075	-0.0095	0.0278	0.0214	0.0158
BAG	0.0453	0.0657	0.0884	0.0208	0.0172	0.0193	0.0448	0.0693	0.0594	0.0354	0.0421	0.07	0.0831	0.027	0.088	0.0497	0.0657
BNBA	0.03	0.0701	0.0707	0.0234	0.01	0.005	0.0422	0.018	0.0786	0.0245	0.0715	0.051	0.0311	0.0417	0.072	0.0011	0.0451
BVIC	0.0343	0.0939	0.0863	0.0395	-0.0319	0.0276	0.0108	0.0319	0.0653	0.0045	0.0439	0.0588	0.0698	0.0434	0.0333	-0.0008	0.0485

	SDRA	BACA	AGRO	CCBI	BBKP	MNC	QNB	BAG	BNBA	BVIC
SDRA	1									
BACA	0.0056	1								
AGRO	-0.0022	0.0197	1							
CCBI	-0.0279	0.0085	0.0996	1						
BBKP	0.0141	0.0278	0.1101	0.0917	1					
MNC	0.0112	-0.0155	0.0627	0.0322	0.1784	1				
QNB	0.0361	0.0057	0.0347	0.0168	-0.0013	0.0037	1			
BAG	-0.0182	0.0069	0.0986	0.0433	0.025	0.0761	0.0087	1		
BNBA	0.0188	0.0296	0.0557	0.0753	0.0902	0.045	0.0129	0.0147	1	
BVIC	0.033	-0.0007	0.0922	0.041	0.0236	0.0526	0.0178	0.0715	0.0254	1

5.4.2 Empirical Analysis

5.4.2.1 Principal Component Analysis

As discussed in Section III. B, when a small number of institutions' principal component variance could explain the volatility within the market, the system is highly interconnected, which is stated in the condition as $h_n > H$. Following Billio et al. (2012), to assess the time variation of h_n, we could detect the accumulation of interconnectedness or correlation and integration contributing to systemic risk. The cumulative risk fraction represented by eigenvalues is exhibited in Figure 5.1.

The first three components in the sample (represented as PC1, PC2 and PC3) could explain a significant portion of the variance. The escalation proportion conveys that intercorrelated exposures within sample banks are also increasing and becoming more persistent. The highest linkage was found in early 2012 between PC1 and PC3 (this connection represents around 44% of return variation), followed by the end of 2014 (35%).

Additionally, the eigenvalue component loading plot shows the explained variance centred around three to four groups of banks. BRI, BMRI, BCA and BTN are grouped in the same section on the right side of the plotting picture. These outcomes suggest that some banks have closer interconnectedness than others through inter-financial assets or inter-financial liabilities exposures. Bank supervisors could also classify the grouping and adjust it to suit their routine banks' monthly report analyses. Noticeable patterns of movements are also detected along the curve: PC1-PC3 has co-movement return (see Figure 5.1.). It would be interesting to gather more data over a longer period of observation that includes both the global financial crises that occurred in 2007 and 2008 and crises brought about by Covid-19.

According to Table 5.5, for eigenvalue λ_k, Comp1-Comp3 work in the same direction shown in Figure 5.1. For instances in Comp1, the three biggest contributors are BCA, BRI and BMRI, with 32.69%, 38.79%, and 39.75% (all of these are classified as KBMI 4). Comp2 conveys contributions by Maybank and BNLI of 47.1% and 28.75%. Moreover, in Comp3, the estimated contributions of NISP, SDRA and MAYA are 43.26%, 34.08% and 32.59%.

The Comp1-Comp3 benefactor appears to come from large banks (KBMI 4 and KBMI 3) with the exception of SDRA (KBMI 2) in Comp3. According to Billio et al. (2012), a high PCA score indicates high interconnectedness risk within the banking system. Specifically, owing to the dominance of big banks, bank policy makers are beneficial by scrutinising the correlated exposures among them. The dominance of big banks is an alluring topic for future research exploring the use of balance sheet variables such as total assets and total equity.

Figure 5.1. Principal Component Analysis

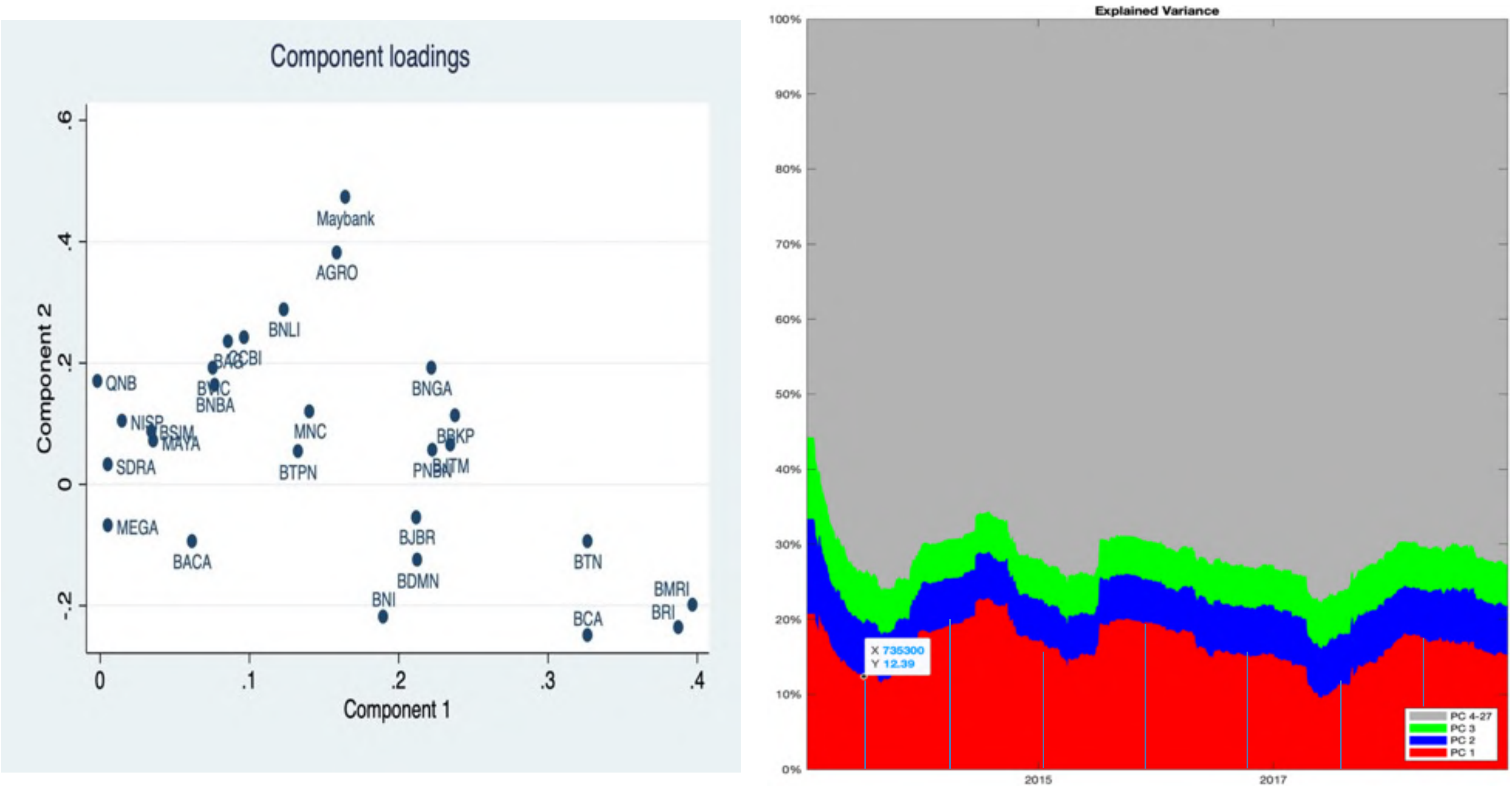


Table 5.5. Principal Component (Eigenvector) – 15 Components

Variabel	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12	Comp13	Comp14	Comp15
BCA	0.3269	-0.2509	0.035	-0.0489	-0.0848	-0.0015	-0.0225	-0.0082	0.1205	-0.0229	-0.0428	-0.0008	-0.0407	-0.033	-0.0033
BRI	0.3879	-0.2372	0.0549	-0.0392	-0.1036	-0.0425	-0.0383	-0.0667	0.054	-0.0066	0.0452	0.0198	0.0317	0.0455	-0.0473
BMRI	0.3975	-0.1991	0.0808	-0.0165	-0.0828	-0.0015	-0.0519	-0.0645	0.0325	0.0177	0.0253	-0.0136	0.0128	-0.0263	-0.053
BNI	0.1901	-0.2189	0.1566	0.0788	-0.2332	-0.0342	0.0539	-0.1442	-0.0473	-0.1266	0.1501	-0.1266	-0.1661	0.0816	-0.2348
MEGA	0.0059	-0.0692	-0.0211	0.245	0.0055	0.6227	0.2463	-0.0522	0.2243	-0.0381	-0.2594	-0.0075	0.0096	0.5271	0.0434
MAYA	0.0363	0.0701	0.3259	-0.3459	0.0916	-0.1353	-0.1921	0.0324	0.3373	0.1721	-0.3674	0.1121	0.546	0.0603	-0.069
BNLI	0.1234	0.2875	0.0688	0.2179	-0.0383	-0.2277	0.0765	0.2286	0.0762	-0.394	-0.2315	0.2074	-0.109	0.1495	0.0698
BDMN	0.2131	-0.1268	0.0417	-0.0475	-0.1616	0.1207	-0.1196	0.0425	0.2302	-0.1048	0.0746	0.1213	0.008	-0.0531	0.4156
PNBN	0.2227	0.0546	-0.0219	0.0591	0.0191	-0.1053	0.2045	0.1981	-0.2308	-0.0618	-0.1599	0.1924	0.1044	0.1053	-0.2945
NISP	0.0153	0.104	0.4326	0.3311	0.2133	0.2792	-0.2023	-0.2085	0.0722	0.032	-0.1538	-0.1977	-0.1425	-0.3737	-0.2587
BNGA	0.2224	0.19	-0.1735	0.1563	-0.1159	-0.1352	-0.035	0.2065	0.1455	0.0875	0.0312	-0.2472	-0.0771	-0.1459	-0.06
BTPN	0.1328	0.0523	0.1398	-0.3382	-0.1058	-0.0141	0.3185	0.2166	-0.079	0.0904	-0.2685	0.0826	-0.4038	-0.1439	0.1897
Maybank	0.1645	0.4711	-0.1916	0.0353	-0.0194	0.0188	-0.1614	-0.0083	0.1131	-0.2124	-0.0204	-0.2233	0.1062	-0.1274	-0.0026
BJBR	0.2124	-0.0555	-0.1512	-0.0589	0.5244	0.0538	-0.1545	0.0517	-0.1959	0.1785	-0.0384	-0.0559	0.0455	0.1656	0.238
BTN	0.3269	-0.0952	0.0698	0.0616	0.0976	-0.0108	-0.1086	0.0155	-0.04	0.0774	-0.0348	0.0366	-0.0242	-0.0511	-0.1321
BSIM	0.0345	0.0868	0.0588	0.0996	-0.1375	0.2399	0.0456	0.6352	0.0783	0.3889	0.3777	-0.061	0.178	0.0505	-0.1834
BJTM	0.235	0.0631	-0.09	-0.0209	0.4548	0.0541	-0.0867	0.1008	-0.2103	0.0737	-0.0262	-0.1293	-0.194	0.0712	0.1232
SDRA	0.0056	0.0308	0.3408	-0.1012	0.2399	-0.0783	0.5037	0.0621	0.2871	-0.143	0.1717	-0.4363	0.0338	-0.0922	0.252
BACA	0.0618	-0.095	0.1907	0.4389	-0.1047	-0.0772	0.1125	0.0128	-0.4472	-0.113	-0.0125	-0.0471	0.5046	-0.109	0.3746
AGRO	0.1587	0.381	0.0963	-0.0386	-0.142	0.0243	-0.0878	-0.0811	-0.084	-0.109	-0.1127	-0.0977	-0.0257	0.2804	-0.0888
CCBI	0.0971	0.2408	-0.06	0.1201	-0.2799	-0.0997	-0.1255	-0.3264	0.1467	0.4217	0.0863	-0.0511	-0.0827	0.1584	0.391
BBKP	0.2382	0.1122	-0.2687	0.0957	0.1225	-0.0487	0.1603	-0.0837	0.1764	-0.0431	0.1468	0.0522	0.1345	-0.0634	-0.06
MNC	0.1409	0.1193	-0.236	-0.1976	0.1321	0.264	0.2434	-0.2674	0.0904	-0.2134	0.28	0.2817	0.2259	-0.2159	-0.0897
QNB	-0.0013	0.1687	0.4287	0.1255	0.2348	-0.1354	-0.1219	-0.014	0.0821	-0.0439	0.4746	0.4669	-0.1772	0.2233	0.0429
BAG	0.0861	0.2351	0.1532	-0.1825	-0.1889	0.4709	-0.088	0.0731	-0.2659	0.0022	-0.0151	0.231	-0.0231	-0.3195	0.1779

5.4.2.2 Granger Causality

Granger causality offers several measures of correlated exposure of financial institutions to capture specific characteristics of edges (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020). The outputs of several centrality measures in Figure 5.2 provide the following important pieces of information:

a. *Degree Granger centrality* is the number of edges that point to a node or, in simple terms, "a lot of banks would do transactions via me". Based on the picture. BCA is the main player in Indonesian banking in terms of network adjacency with 1.19. It is followed by BTN and BNGA (1.11 for both) and Maybank (1.07). The number of edges indicates the importance of that bank within the banking system, which could also lead to the substitutability issues that attract the attention of Basel (BCBS 2018). This could also mean that the bank network significantly facilitates other financial institutions' transaction needs such as clearing, RTGS and billing payments.
b. *Closeness centrality* reflects the average shortest edges required to reach nodes interconnectedness through BCA, BRI, BNI, BMRI and BTN. We can translate this context as BCA with a score of 0.84 and BRI at 0.81 collapse, which is catastrophic or vital compared to other banks' failure in terms of triggering systemic crises in Indonesia.
c. *Eigenvector centrality* is translated as not only how many edges but also how many edges really matter. The main player in the Indonesian banking system is BCA, with 0.08, followed by BRI and BNI, with 0.07 each. The next most important bank is BMRI, with a score of 0.06. The score indicates how connected a bank is to the whole banking system.

The dominance of BCA interconnectedness in Indonesia's banking network is profound, as only five banks have no connection. Further, BRI, BMRI and BNI have been empirically shown to be the core banks in Indonesia's banking system. This result is in line with the Granger centrality measures discussed above and suggests that, for banks analysis, policy makers should build on publicly available data or (in our case) stock market data and their returns correlations (see Figure 5.3).

According to the same network matrix, the periphery banks in the system are BVIC, BNBA, CCBI, SDRA and BSIM, all of which are classified as KBMI 1 or small banks. This outcome reinforces the PCA results and would be interesting to explore in future research. An alternative way to correlate the interbank transaction is to use detailed balance sheet data collected by bank supervisors. We will discuss this in the next section using Gai and Kapadia's (2010) model.

Figure 5.2. Centrality Measures

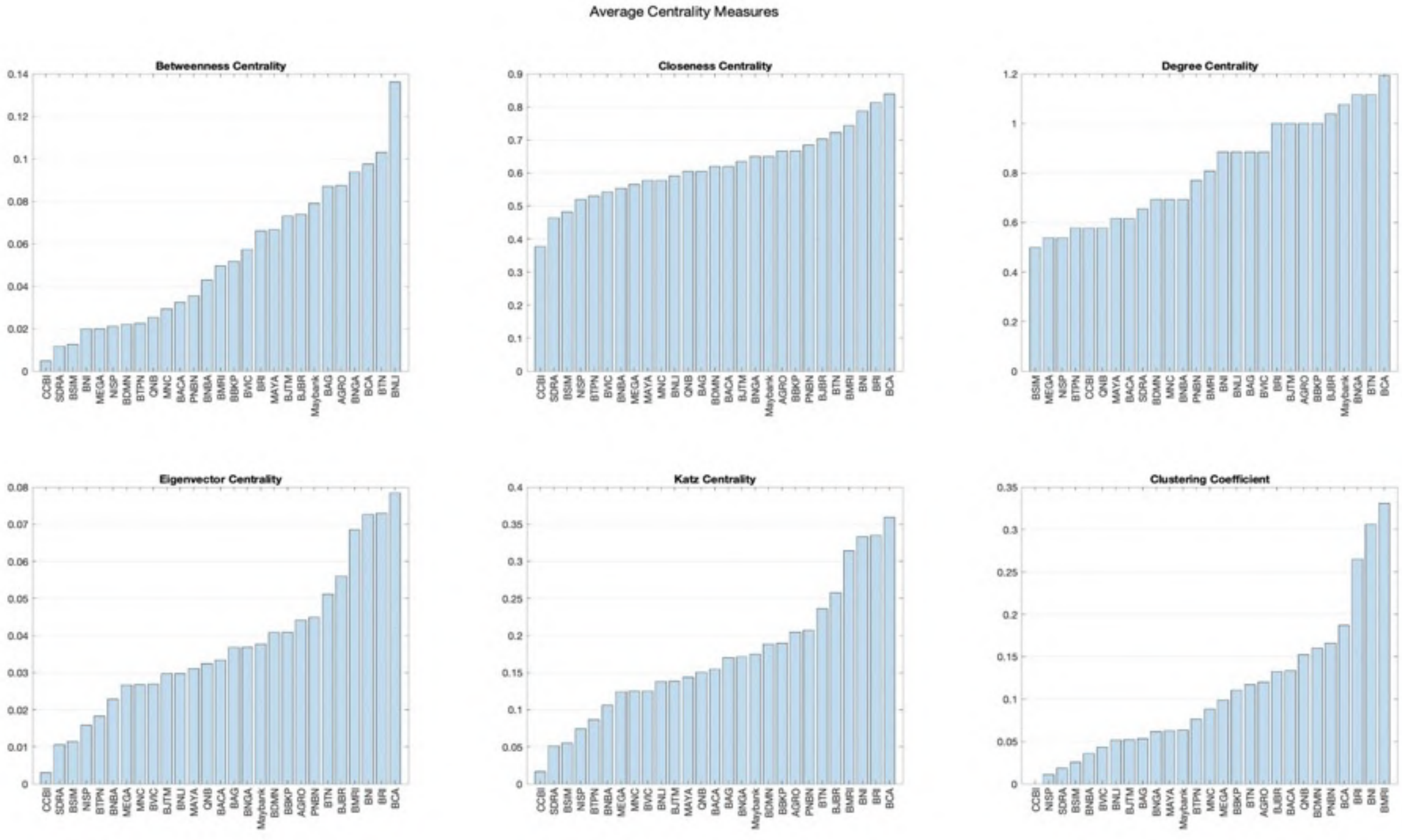
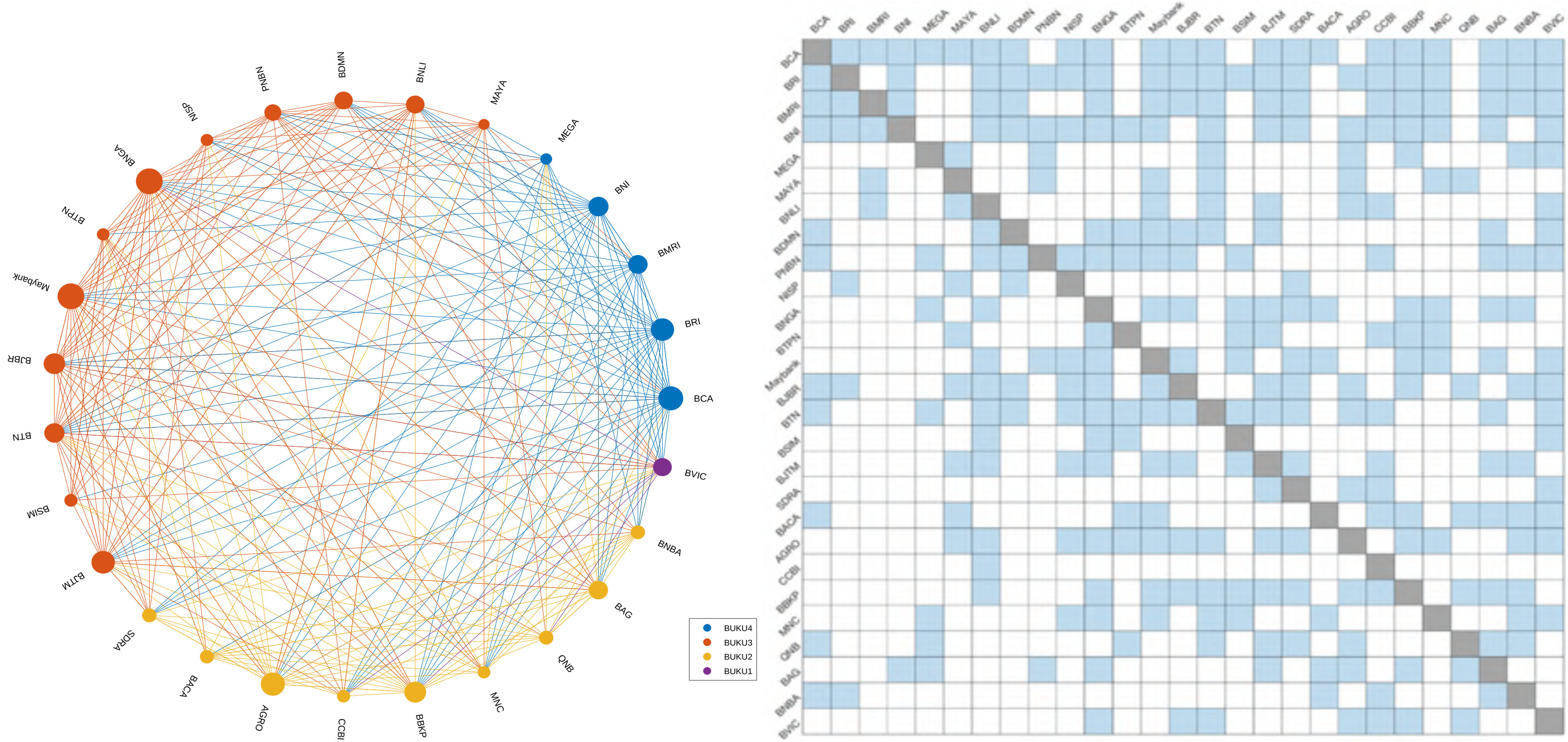


Figure 5.3. Network Matrix and Interconnectedness



According to Billio et al. (2012), the risk direction of systemic events is predicted using Connection In+Out (CIO). This construct refers to the number of other banks that are significantly Granger caused by other neighbour banks (and Granger cause these neighbour banks as well). Meanwhile, Connection In+Out – Other (CIOO) is the sum of the two. Figure 5.4. shows that most of the CIO connection comes from banks' KBMI peers. In the practical application, this indicates how large banks in Indonesia tend to make transactions among themselves. Exposures among dominant banks could increase the severity of systemic shocks if they fail at the same time. The highest Granger caused by is observed at the end of 2014 (with an approximated index of 4.6. An increasing trend was seen at the end of 2019, as Covid-19 cases started to emerge in some countries (Rizwan, Ahmad & Ashraf 2020).

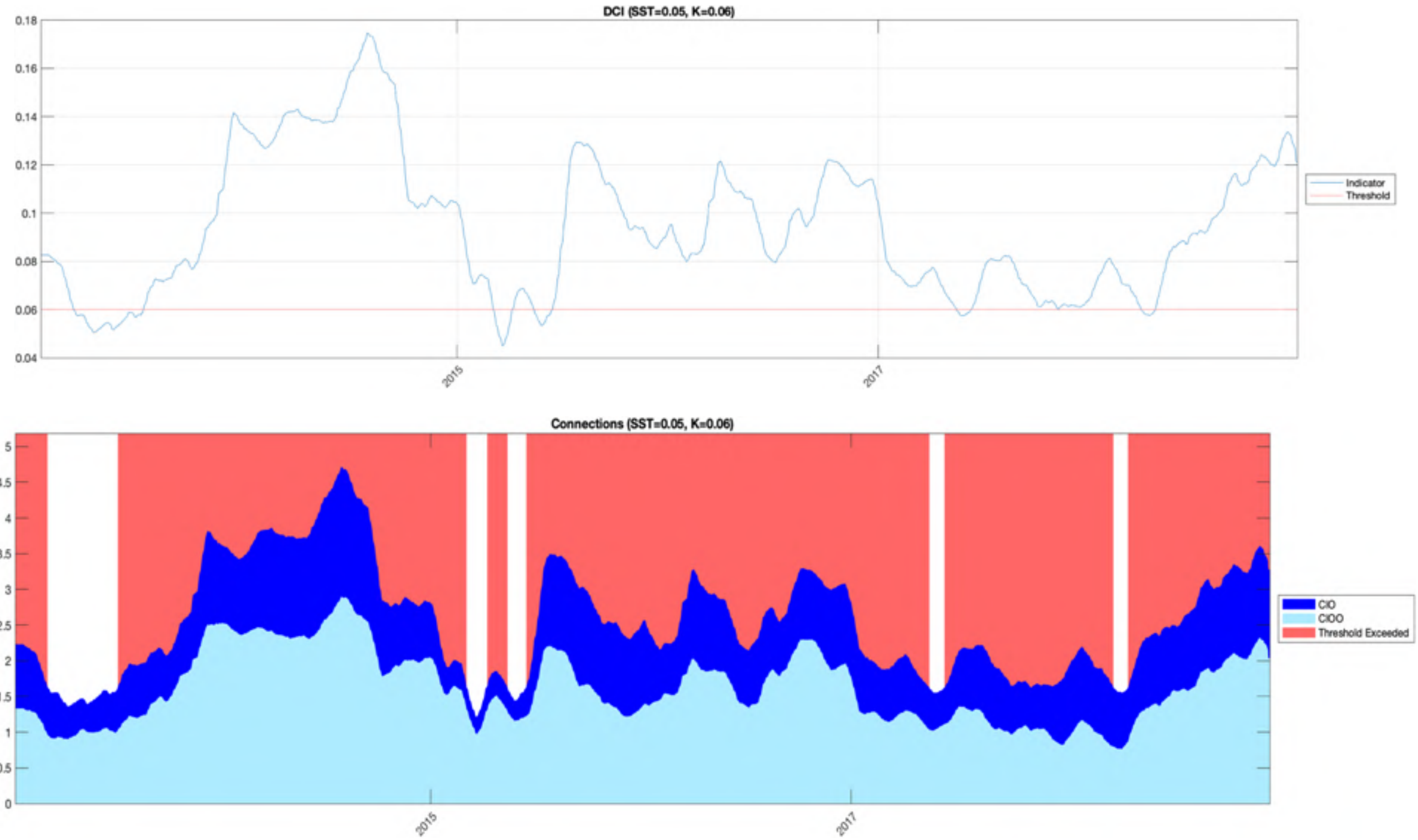
Further, as shown in Table 5.6., when Diebold and Yılmaz (2014) ran tests for different perspectives of system-wide spillover risk between banks and found that BMRI and BRI are the two most connected banks in Indonesia. Though BCA is not at the top of the list, it is in the top five most connected banks in the system (see Robustness Test 1).

Table 5.6. Spillover 5 Banks

	BMRI			BRI			BNI		
	From	To	Sum	From	To	Sum	From	To	Sum
2012	0.6519	0.7728	1.4247	0.5915	0.6049	1.1964	0.4403	0.3160	0.7563
2013	0.6501	0.9828	1.6329	0.6013	0.7483	1.3497	0.2756	0.2176	0.4932
2014	0.7487	1.1595	1.9082	0.7426	1.0823	1.8249	0.6342	0.8831	1.5173
2015	0.6906	1.0225	1.7131	0.6854	0.9909	1.6763	0.6675	0.9723	1.6398
2016	0.6920	0.9871	1.6791	0.6939	0.9620	1.6559	0.6663	0.9816	1.6479
2017	0.6019	0.8395	1.4414	0.5956	0.8410	1.4367	0.5545	0.7089	1.2635
2018	0.5825	0.7398	1.3223	0.5761	0.7467	1.3228	0.5609	0.6604	1.2213
2019	0.6899	0.9392	1.6290	0.6873	0.8884	1.5758	0.6898	0.9293	1.6191

	BTN			BCA		
	From	To	Sum	From	To	Sum
2012	0.6145	0.6540	1.2684	0.4845	0.4611	0.9456
2013	0.5428	0.6312	1.1739	0.5698	0.7354	1.3053
2014	0.6638	0.7522	1.4159	0.6940	0.9587	1.6526
2015	0.5801	0.6207	1.2008	0.5821	0.6063	1.1885
2016	0.5736	0.6061	1.1797	0.6444	0.7836	1.4279
2017	0.4986	0.5877	1.0863	0.4805	0.4998	0.9803
2018	0.4839	0.5543	1.0382	0.4812	0.4795	0.9607
2019	0.6459	0.8129	1.4587	0.5648	0.5657	1.1305

Figure 5.4. Connection Indicator



5.4.2.3 Balance Sheet Stylised Fact Network Model

In the network theory model, nodes represent banks or financial institutions. The nodes interact through edges, depicted as node interconnections (Eisenberg & Noe 2001; Gai & Kapadia 2010). The edges could stem from interbank assets or interbank liabilities and securities such as the sub-prime mortgage that was introduced during the financial crises in 2007 and 2008. Each bank manages its liquidity to assess the cash and finance its operations as explained in this section's introduction.

Interbank assets A^{IB}	Interbank liabilities L^{IB}
Other assets A^{M}	Deposit – D
	Equity – K

To model the interconnectedness based on the stylised fact of bank balance, we employ the network model proposed by Gai and Kapadia (2010).

The bank solvency is $(1-\emptyset)\, A_i^{IB} + qA_i^M - L_i^{IB} - D_i > 0$ or the equation in the other form $\emptyset < \frac{K_i-(1-q)A_i^M}{A_i^{IB}}\ for\ A_i^{IB} \neq 0$, where $K_i = A_i^{IB} + A_i^M - L_i^{IB} - D_i$ is the capital buffer. For the crises to spread to other banks in the system $\frac{K_i-(1-q)A_i^M}{A_i^{IB}} < \frac{1}{j_i}$. Bank with in-degree j is vulnerable, with $v_j = P\left[\frac{K_i-(1-q)A_i^M}{A_i^{IB}} < \frac{1}{j}\right], where\ j \geq 1$ and joint degree distribution of vulnerable bank $G(x,y) = \sum_{j,k} v_j \,.\, p_{jk} \,.\, x^j \,.\, \mathrm{y}^{\mathrm{k}}$.

We know that the interbank assets of one bank will equal the interbank liabilities of its counterpart. Average in-degree (1/n) $\sum_i j_i = \sum_{j,k} jp_{jk}$ equals the average out-degree (1/n) $\sum_i k_i = \sum_{j,k} kp_{jk}$

$z = \sum_{j,k} j\, p_{jk} = \sum_{j,k} k\ p_{jk}$. From $G(x,y)$ for the link dispersed from a randomly chosen vulnerable bank is $G_0(y) = G(1,y)$

$$= \sum_{j,k} v_j \,.\, p_{jk} \,.\, \mathrm{y}^{\mathrm{k}}$$

Moreover, for $G(1,1) = G_0(1)$

$$= \sum_{j,k} v_j \,.\, p_{jk}$$

If financial instability does propagate, we define $v_j . r_{jk}$ as the degree distribution of a random vulnerable bank. If there are many in-degree or links to one bank, then there is a higher probability jp_{jk} for it to be the network counterpart of the chosen bank. The number of outgoing placements that leave the vulnerable bank of the randomly chosen bank is calculated as

$$G_1(y) = \sum_{j,k} \quad v_j . r_{jk} . y^k \ = \frac{\sum_{j,k} \quad v_j . j . p_{jk} . y^k}{\sum_{j,k} \quad j . p_{jk}}$$

Bank supervisors or policy makers have the privilege to access the banks' detailed data. The advantage of using the balance sheet richness value is that it provides a clear idea of the interconnectedness network between banks. The application could also simulate using the capital buffer of related banks.

5.4.2.4 Basel Indicator-Based Method

The Basel methodology is simple to calculate, as prudential data is gathered and submitted by the banks. Despite its simplicity, Basel results are more robust than those of approaches that rely on market variables (BCBS 2018). Owing to the secrecy of the detailed bank balance sheet data, we code the banks with IDs while keeping the information traceable for our analysis purposes.

This section focuses on the interconnectedness category of the Basel indicator-based methodology adjusted to the country's needs (OJK 2018). For all categories, the Basel indicator-based method emphasises the proportion of the size of bank *i* to that of the entire banking system $\sum_{ij}^{N}$. In the analysis, the interconnectedness category based on the Basel method provides no information about how the overlapping exposure triggers systemic risk.

Our calculations have been streamlined to focus on the period from 2016–2018 and sorted according to their importance score of interconnectedness, which is the average of interbank assets, interbank liabilities and securities outstanding.

Table 5.7. Basel Outcomes Sorted by Interconnectedness Score

No.	Name	Interbank Assets	Interbank Assets	Securities Out.	Size	Intercon.	Substit.	Systemic Score
Dec-18								
1	BANK 1	556	963	2304	**1333**	1274	865	**1158**
2	BANK 6	815	164	2724	**1028**	1234	976	**1079**
3	BANK 2	903	746	1871	**1336**	1173	1147	**1219**
4	BANK 3	658	646	813	849	706	723	759
5	BANK 73	109	783	276	307	389	103	266
6	BANK 8	635	195	173	261	334	145	247
7	BANK 37	251	614	129	125	331	56	171
8	BANK 4	357	213	292	210	288	300	266
9	BANK 19	811	49	0	271	287	390	316
10	BANK 9	242	264	208	359	238	518	372
Dec-17								
1	BANK 1	556	963	2304	**1333**	1274	865	**1158**
2	BANK 6	815	164	2724	**1028**	1234	976	**1079**
3	BANK 2	903	746	1871	**1336**	1173	1147	**1219**
4	BANK 3	658	646	813	849	706	723	759

No.	Name	Interbank Assets	Interbank Assets	Securities Out.	Size	Intercon.	Substit.	Systemic Score
5	BANK 73	109	783	276	307	389	103	266
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7	BANK 37	251	614	129	125	331	56	171
8	BANK 4	357	213	292	210	288	300	266
9	BANK 19	811	49	0	271	287	390	316
10	BANK 9	242	264	208	359	238	518	372
Dec-16								
1	BANK 2	964	921	1939	**1353**	1274	1118	**1248**
2	BANK 1	453	930	2274	**1327**	1219	800	**1115**
3	BANK 6	652	117	2795	**1000**	1188	1066	**1084**
4	BANK 3	855	622	782	811	753	687	750
5	BANK 73	101	696	175	277	324	108	236
6	BANK 8	704	88	166	266	319	164	250
7	BANK 37	203	616	110	124	310	54	162
8	BANK 19	827	67	0	270	298	431	333
9	BANK 4	389	185	284	229	286	285	267
10	BANK 9	277	222	153	365	217	481	355

Table 5.7. indicates that estimations of 'central bank' per market data are not significantly better than the Basel outcomes. Though BCA superiority is not fully portrayed by Basel size intense calculation, the bank still appeared in the top five Indonesian SIBs. Moreover, BMRI, BRI, BNI and BTN appear interchangeably during the estimation window. This result indicates that capital market data could also resemble Basel interconnectedness, if not the overall SIB rankings in the Indonesian context. Our findings are consistent with the work of Salim and Daly (2021), who recently modelled SIBs using market data vis-à-vis the Basel prudential guidelines.

5.5 Conclusion and Policies Implication

This chapter investigates how stock market data, namely, share price, market capitalisation and asset returns, could be used to analyse the interconnectedness within a financial system. Our data on Indonesian banking from 2012–2019 employ Billio et al.'s (2012) principal component analysis and Granger causality. The analysis also considers the Basel indicator-based guideline to compare the interconnectedness scores. The findings show that returns in co-movements exist in the Indonesian banking system, which indicates interconnectedness. The Eigenvalue plot of the PCA method exhibits how the first three principal components could seize a significant portion of the variance. The outcome envisages an increased risk of commonality and interconnection in the financial system. Further, the finding confirms that the main benefactor contributors to the principal banks are categorised as KBMI 4 and KBMI 3.

Granger causality stresses the importance of intercorrelated exposure to SIB identification and traces how risk might spread throughout the system. The degree of Granger, closeness, and eigenvector centrality shows that BCA, BRI, BNI, BMRI and BTN are the core banks in the Indonesian banking network, and their collapse would be catastrophic. Based on the same centrality measures, the results also reveal that most KBMI 2 banks are in the network periphery. Moreover, the outcome raises the issue of substitutability because of their multi connections in the system wide.

Per our research objective, we also compare the model results with the Basel interconnectedness score based on prudential balance sheet data. The supremacy of KBMI 4 and KBMI 3 banks is in line with the Basel indicator-based data that use prudential data as employed by policy makers (OJK 2018). Our findings are consistent with those of Salim and Daly (2021), who recently modelled SIBs.

We recommend that future research extends the estimation period to cover the global financial crises of 2007–2008, as well as the period after Covid-19's effects on systemic risk. It would also be worthwhile to explore additional balance sheet details and understand their connection altogether. Finally, the findings suggest that bank supervisors should monitor risk escalation and perform risk mapping using capital market and asset returns data. The outcomes would also help policy makers monitor interconnectedness among core bank networks that could trigger systemic risk.

A. Robustness Test

1. Variance Decomposition

Diebold and Yılmaz (2014) define pairwise direction connectedness from j to i $C^H_{i \leftarrow j} = d^H_{ij}$, where $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i} 1$. Net pairwise $\frac{N^2-N}{2}$ is analogous to bilateral interbank balances. The off-diagonal row is labelled 'from', and the column is labelled 'to' in the connectedness table.

	X_1	X_2	$\cdots$	X_N	From others
X₁	d^H_{11}	d^H_{12}	$\cdots$	d^H_{1N}	$\sum_{j=1}^{N} d^H_{1j},\ j \neq 1$
X₂	d^H_{21}	d^H_{22}	$\cdots$	d^H_{2N}	$\sum_{j=1}^{N} d^H_{2j},\ j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
X_N	d^H_{N1}	d^H_{N2}	$\cdots$	d^H_{NN}	$\sum_{j=1}^{N} d^H_{Nj},\ j \neq N$
To others	$\sum_{i=1}^{N} d^H_{i1}$ $i \neq 1$	$\sum_{i=2}^{N} d^H_{i1}$ $i \neq 2$	$\cdots$	$\sum_{i=1}^{N} d^H_{iN}$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1}^{N} d^H_{ij}$ $i \neq j$

define total directional connectedness from others to i *as* $C^H_{i \leftarrow \circ} = \sum_{j=1}^{N} d^H_{ij}\ \ j \neq i$

and the opposite of total directional connectedness to others from j as $C^H_{\circ \leftarrow j} = \sum_{i=1}^{N} d^H_{ij}\ \ i \neq j$

The grand total off-diagonal entries, equivalent to the sum of 'from' and 'to', measures total connectedness $C^H = \frac{1}{N}\sum_{i,j=1}^{N} d^H_{ij}\ \ i \neq j$.

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Chapter 6: Asset Returns as a Proxy of Risk and Interconnectedness: US Evidence

We further explore how asset returns could be a good proxy to detect interlinkages in the financial system. This chapter employs a US dataset for the 2002–2019 period. Pairwise returns correlation indicate the interconnectedness at the preliminary stage. PCA captures a significant portion of variance and detects the co-movement and highly connected state of the financial market during crises. Granger centrality tested with pairwise directional variance decomposition indicates the importance of banks and insurance companies in the US financial system. This chapter recommends policymakers use multiple network models to validate and calibrate the SIFIs list.

6.1 Introduction

We found in the previous chapter that market data could be a good proxy to identify the central bank in the banking network, risk built up and interconnectedness in the system. The endogenous effects of intercorrelated exposure as stated in the balance sheet are catastrophic and could trigger bank failure and create systemic risk. The nature of interconnectedness is difficult to avoid, since interbank borrowing and lending are common in banks' daily operational activities. These serve to manage extra cash and source liquidity shortage, which keeps the banks running and earns interest as their main income. This chapter extends our investigation to the effect of correlated exposures across industries. The previous chapter explored risk mapping and correlation in a specific commercial bank sector, while the present chapter extends this to include insurances, government support entities, and separate classes of investment and commercial banks. To account for multiple sectors in one broad calculation is highly relevant, as we know that contagion effect encompasses multiple industries during financial crises.

Allen and Gale (2000) indicate how market structure completeness could affect financial contagion. Although their data focused on banking, it partly showed that risk allocation to other industries could be a way to mitigate systemic risk. The global financial crises in 2007–2008 provide an excellent sample, including the failure of Lehman Brothers triggered by subprime mortgage investment losses, insurances companies AIG and Prudential due to risk transferred through contracts and credit default swap mechanism, and government support entities in the housing sector such as Fannie Mae and Freddie Mac. Much research has discussed systemic institution effect using banks' data or operational assumptions to propose models. Pre-global financial crises examples are Allen and Gale (2000); Freixas, Parigi and Rochet (2000); Eisenberg and Noe (2001); Lehar (2005); Nier et al. (2007); Elsinger, Lehar and Summer (2006a); and Elsinger, Lehar and Summer (2006b). Post-global financial crises examples are Acharya (2009), Gai and Kapadia (2010), Krause and Giansante (2012), Billio et al. (2012), Brämer and Gischer (2013), Drehmann and Tarashev (2013), Pais and Stork (2013), Akhter and Daly (2017), Daly et al. (2019) and Salim and Daly (2021). Although banking is the dominant force in many countries' economies, incorporating other industries into one analysis package could provide a more comprehensive picture of risk pattern and contagion effect.

This chapter raises the questions of: 1) Can market data (e.g., share price and asset returns) indicate risk in the financial system and interconnection?, 2) What financial companies or sectors are dominant and systemic in the economy?, and 3) How are the results compared to the pairwise directional variance decomposition outcome? To answer these questions, we follow Billio et al.'s (2012) method of using PCA to scale the risk commonality and risk direction. This chapter also uses Granger causality to scrutinise SIFIs across the entire economic system. In the latter part of our analysis, we also compute spillover among entities using Diebold and Yılmaz (2014) to calibrate the method. Outcomes from this research will broaden our views on systemic risk and interconnectedness, risk spread and escalation both from and to sectors. The results will benefit regulators in making policy judgements and provide insight to calibrate and validate measurements of comprehensive risk in the financial system.

The findings of this chapter are as follows:

1. Pairwise returns correlation is significant at the 5% confidence level and indicates the interconnectedness and co-movement.
2. The first three principal components of PCA capture the notable portion of the returns variance. The outcome shows a highly interconnected state in the US financial market during financial crises, in which the banking sector is the key player. It is also confirming the theory where in majority cases the PCA is always efficient across the first three planes (or dimensions) and then become less efficient from the fourth component and higher.

3. Granger centrality methods indicate the dominance of banks and insurance companies in the US financial network, with this result being consistent both during and after crises.
4. SIBs are noted using pairwise direction variance decomposition and broadly in line with Granger centrality results. Use of multiple methods to validate SIFIs could aid policymakers.

This chapter is structured as follows. Section 6.2 reviews the literature and highlights the importance of the network model approach in systemic risk study, Section 6.3 details the methodology used, Section 6.4 presents the analytical results and interpretation, and Section 6.5 draws conclusions and makes policy recommendations.

6.2 Literature Review

'Systemic risk' is defined as a risk of disruption to financial services caused by an impairment of all or parts of the financial system, with potential negative consequences for the real economy (FSB, IMF & BIS 2009). ECB (2009a) defines systemic risk as the risk of financial instability that impairs the functioning of a financial system to the point that economic growth and welfare suffer significantly. From the researcher perspective, De Bandt and Hartmann (2000) define systemic risk as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. Other definitions include intercorrelated exposures (Acharya et al. 2017) and a set of circumstances that threatens the stability of public confidence in the financial system (Billio et al. 2012). In short, there is no broad consensus on a single definition of systemic risk, but we can infer from all definitions that they would include the collapse of SIFIs or 'too big to fail' financial entities, the resulting system contagion, system-wide effects and economic downturn as systematic risk.

Systemic risk studies use different model estimations, data and variables, as classified by Bisias et al. (2012), who segregate studies in this area by scope, variables employed and research method. Example papers using a cross-section analysis are Adrian and Brunnermeier (2016) (who used CoVaR to estimate the VaR of banks and its risk contribution to the whole system; CoVaR is the difference of the financial system VaR condition when firm i is in the financial distress versus the financial system VaR when firm i is in a median state); Acharya et al. (2017) (who used MES and SES to measure financial institutions' expected losses when the market falls below a predefined threshold over a given time horizon); and Brownlees and Engle

(2017) (who introduced SRISK to capture the expected capital shortage of a firm given its degree of leverage and MES as the expected loss an equity investor in a financial firm would experience if the overall market declined substantially). Estimation of capital shortfall uses bivariate daily equity returns of firms and market index, where volatilities follow asymmetric GARCH and DCC processes. Cross-section analysis in systemic risk is popular among scholars, as it is relatively simple and uses publicly available capital market data.

Our study employs the network model approach to measure the interconnectedness among financial entities. Prior studies have mapped the interlinkages between banks and their failure impact on other sectors such as insurance companies. Prominent papers that used the network approach include Allen and Gale (2000); Eisenberg and Noe (2001); Gai and Kapadia (2010); Gai, Haldane and Kapadia (2011); Nier et al. (2007); Krause and Giansante (2012); and Billio et al. (2012). In the network theory model, nodes represent entities or institutions. The nodes interact through edges (Eisenberg & Noe 2001; Gai & Kapadia 2010), which arise as consequences of overlapped assets or liabilities, such as risk transfer activities from banks to insurance companies (e.g., subprime mortgages before and during the 2007–2008 global financial crises). Gai and Kapadia (2010) model bank solvency as $(1-\emptyset)\ A_i^{IB} + qA_i^M - L_i^{IB} - D_i > 0$ or in the other form $\emptyset < \frac{K_i-(1-q)A_i^M}{A_i^{IB}}\ for\ A_i^{IB} \neq 0$, where $K_i = A_i^{IB} + A_i^M - L_i^{IB} - D_i$ is the capital buffer. For the crisis to spread to other banks in the system, $\frac{K_i-(1-q)A_i^M}{A_i^{IB}} < \frac{1}{j_i}$.

Allen and Gale (2000), in their prominent study on systemic risk, demonstrated that market structure is important for understanding systemic risk effect. Their findings show that when the market structure is complete, where all participants have edges to others in the network, the market is more resilient to financial shock than an incomplete market. They explain that some portions of shocks are distributed to many participants in the system. A wider system is more robust compared to only one institution absorbing all the counterpart failure.

Eisenberg and Noe (2001) proposed the general model of clearing system. The clearing vector represents the payments from nodes to others in the financial system. It simulated the conditions of proportional repayments of liabilities in default, limited liability of equity and absolute priority of debt over equity. Cont, Moussa and Santos (2013) investigated Brazilian banks, employing the balance sheet and network structure in 2007–2008 and failed banks' contribution to systemic risk. They came up with the Contagion Index as a metric for the systemic importance of institutions. This measures the expected loss to the network triggered by the default of an institution in a macroeconomic stress scenario. Krause and Giansante

(2012) developed a model of interbank loans given and received by banks of different sizes. In their findings, the size of a failing bank has limited effect on the number of banks affected by contagion. They concluded that banks' network structure has a much more significant effect on systemic risk. Elsinger, Lehar and Summer (2006a) extended the model used by Eisenberg and Noe (2001) to include uncertainty to quantify the correlated exposure and domino effect, and Elsinger, Lehar and Summer (2006b) analysed the network analysis correlated exposure and mutual credit relation that may cause domino effect. As discussed previously, most network studies develop models based on banking operation activities assumption.

Our study explores how financial entities' variance could explain the risk build up, identify SIFIs and explain how risk propagates within a network. Instead of focusing on one specific banking class (like the majority of network model studies of systemic risk), our analyses encompass other financial institutions like insurance companies, commercial banks, investment banks and government support entities. This study aims to highlight the interconnection by employing PCA and Granger causality, following Billio et al. (2012). We build on the extant research through model outcome and prove that 'central bank' status is not solely a matter of size. The results are useful for policymakers to monitor and mitigate systemic risk and connection path failure in both the banking sector and whole financial system.

6.3 Data and Methodology

6.3.1 Data Source

The datasets represent all financial sectors listed on the New York Stock Exchange in the period 2002–2019. The datasets encompass commercial banks, investment banks, insurance companies and government support entities. As we examine SIFIs, we select 20 major financial institutions as representative of each sector—six investment banks (IB), seven commercial banks (CB), five insurance companies (IC) and two government support entities (GSE).

We collate the data of share price (daily), trading volume (daily), outstanding shares (daily), market capitalisation (daily), total assets and equity (quarterly), and separate accounts for insurance companies (quarterly). There are also states variables such as the Fed fund rate, VIX index, and some like T-bill delta, and excess returns. Data was sourced from the Eikon Thomson Reuters databases compiled by Belluzo (2020). MATLAB R2021a was used for analyses.

We use three methods. First, we use PCA to measure the interconnectedness of asset returns of US financial institutions. PCA has the advantages of reducing data dimension, increasing interpretability and minimising information loss (Jolliffe & Cadima 2016). PCA can also detect the risk of large financial institutions' failure (Baek, Cursio & Cha 2015; Billio et al. 2012). Second, we employ Granger causality to evaluate the risk spread direction among banks. This consists of several network indicators: degree of causality, number of connections, closeness and eigenvector centrality. Granger causality allows scholars to map those institutions that could trigger systemic risk within a financial network (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020; Zheng & Song 2018). For PCA and Granger causality, we follow Billio et al.'s (2012) methodology.

6.3.2 Principal Component Analysis

High-frequency data and PCA as an adaptive descriptive statistic are used in many research fields. PCA has been used to analyse systemic risk in Billio et al. (2012); Fang et al. (2018); and Baek, Cursio and Cha (2015). We follow Billio et al. (2012) in measuring the degree of interconnectedness of asset returns of financial institutions into orthogonal factors of decreasing explanatory power:

R^i = stock return of institutions *i*, *i=1,….,N,* system aggregate return $R^s = \sum_i R^i$, $E[R^i] = \mu_i$ and $Var[R^i] = \sigma_i^2$ to have:

$$\sigma_s^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_i \sigma_j \, E\left[z_i \, z_j\right]$$

$$Z_k \equiv \frac{\left(R^k - \mu_k\right)}{\sigma_k} \quad k = i, j$$

where z_k is the standardised return of institutions *k* and σ_s^2 is the variance of the system. If we put λ_k the *k*-th eigenvalue with *N* zero mean uncorrelated variables:

$$\mathrm{E}\,[\zeta_k \zeta_l] = \begin{cases} \lambda_k & if\ k = 1 \\ 0 & if\ k = 0 \end{cases}$$

$$Z_i = \sum_{k=1}^{N} L_{ik} \, \zeta_k$$

where L_{ik} is a factor loading for ζ_k for institutions *i*. Then we have:

$$\mathrm{E}\left[Z_i Z_j\right] = \sum_{k=1}^{N} \sum_{l=1}^{N} L_{ik} L_{jl} \, \mathrm{E}\,[\zeta_k \zeta_l] = \sum_{k=1}^{N} L_{ik} L_{jk} \lambda_k$$

$$\sigma_s^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k$$

We focus on subset n < N, as this set captures most of the volatility during crises and indicates the increase of interconnectedness among banks. If total risk of the system is defined as $\Omega \equiv \sum_{k=1}^{N} \lambda_k$ and $\omega_n \equiv \sum_{k=1}^{N} \lambda_k$, the risk associated with the first principal components is $\frac{\omega_n}{\Omega} \equiv h_n \geq H$. The contribution, $PCA_{i,n}$, of institution *i* to system risk is:

$$PCAS_{i,n} = \frac{1}{2}\frac{\sigma_i^2}{\sigma_S^2}\frac{\vartheta\sigma_S^2}{\vartheta\sigma_i^2} \mid h_n > H$$

$$PCAS_{i,n} = \frac{1}{2}\frac{\sigma_i^2}{\sigma_S^2}\frac{\vartheta\sigma_S^2}{\vartheta\sigma_i^2} \mid h_n \geq H = \sum_{k=1}^{N} \frac{\sigma_i^2}{\sigma_S^2} L_{ik}^2\, \lambda_k \mid h_n \geq H$$

6.3.3 Granger Causality

Using Granger causality (in conjunction with the network approach) builds on its ability to predict the forecast of value based on other time series past information. In the capital market where frictions exist, Granger causality appears in the assets return based on other institutions' returns, indicating the spillover risk (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020; Zheng & Song 2018). We use Granger causality to evaluate the direction of risk spreading in a financial system during crises. Please refer to Billio et al. (2012) for the complete formula description:

$$(j \to i) = \begin{cases} 1 & \text{if j Granger causes i} \\ 0 & \text{otherwise} \end{cases}$$

The interconnectedness measures consist of:

f. *Degree of Granger causality* (DGC)—measures the association of N(N–1) pairs of N banks:

$$DGC \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq 1} (j \to i)$$

g. *Number of connections*—captures the importance of banks during the systemic event:

$$\#Out\colon (j \to S) | DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} (j \to i) | DGC \geq K'$$

$$\#In\colon (S \to j) | DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} (i \to j) | DGC \geq K'$$

$$\#In + Out\colon (j \leftrightarrow S) | DGC \geq K = \frac{1}{2(N-1)} \sum_{i \neq j}^{N} (i \to j) + (j \to i) | DGC \geq K'$$

where *S* = system, *#Out* = number of banks Granger-caused by institution *j*, *#In* = number of banks Granger-caused by institution *j*, and *#In+Out* = the sum of these.

h. *Sector-conditional connections*—used to analyse types of banks that affect other classes:

$$\#Out - to - Other\colon \frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \big((j|\alpha) \to (i|\beta)\big) | DGC \geq K'$$

$$\#In-from-Other\text{: } \frac{1}{\frac{(M-1)N}{M}} \sum_{\beta\neq\alpha} \sum_{i\neq j} \left((i|\beta) \to (j|\alpha)\right)|DGC \geq K'$$

$$\#In+Out-Other\text{: } \frac{\sum\beta\neq\alpha\sum i\neq j\left((i|\beta)\to(j|\alpha)\right)+\left((j|\alpha)\to(i|\beta)\right)\ |DGC \geq K'}{2(M-1)N/M}$$

where M = banks KBMI 1–4, *#Out-to-Other* = number of banks KBMI Granger-caused by institution j, *#In-from-Other* = number of banks KBMI Granger-cause institution j, and *#In+Out-Other* = the sum of these.

i. *Closeness*—estimates the shortest edges between financial institutions:

$$C_{jS}|_{DGC\geq K} = \frac{1}{N-1}\sum_{i\neq j} C_{ji}\left(j \overset{C}{\to} i\right)|DGC \geq K'$$

j. *Eigenvector* centrality—signal of bank significance within the network based on its connection to other banks:

$$V_j|_{DGC\geq K} = \sum_{i=1}^{N} [A]_{ji}V_i|_{DGC\geq K'}$$

6.4 Results

6.4.1 Statistics Summary

The datasets are classified into four groups: investment banks (IB), commercial banks (CB), insurance companies (IC) and government support entities (GSE). This sample was compiled and provided by Belluzo (2020), with the MS Excel worksheet containing share price (daily), trading volume (daily), market capitalisation (daily), total assets and equity (quarterly), and US macroeconomic indicators (daily). There are 4,689 daily observations for each variable for the period 2002–2019. The sample period includes several major shocks to global financial markets, such as the dotcom bubble (2001–2002), subprime mortgage crisis (2008–2009), European debt crisis (2010–2011), Russian ruble crisis (2014–2015) and stock market selloff (2015–2016). The sample institutions are listed in Table 6.1.

Table 6.1. US Dataset Sample

No.	Ticker	Institution	Group
1	GS	Goldman Sachs	IB
2	MS	Morgan Stanley	IB
3	BAC	Bank of America	IB
4	C	Citigroup	IB
5	JPM	JP Morgan Chase	IB
6	LEH	Lehman Brothers	IB
7	USB	US Bancorp	CB
8	WFC	Wells Fargo & Co	CB
9	STT	State Street	CB
10	PNC	PNC Financial Services	CB

No.	Ticker	Institution	Group
11	AXP	American Express	CB
12	COF	Capital One Financial	CB
13	BK	Bank of New York Mellon	CB
14	AIG	American International Group	IC
15	ALL	Allstate Corp	IC
16	BRK	Berkshire Hathaway	IC
17	MET	Metlife	IC
18	PRU	Prudential Financial	IC
19	FMCC	Federal Home Loan Mortgage Corp / Freddie Mac	GSE
20	FNMA	Federal National Mortgage Association / Fannie Mae	GSE

To estimate PCA and Granger causality, we use Belluzo's (2020) MATLAB code for systemic risk. Based on analysis of statistics returns, as shown in Table 6.2, we can see that over the sample window, shareholder investment returns are positive except for GSE in 2005–2007 and GSE and CB in 2008–2010 (i.e., financial crises). We know that CB and GSE were two businesses heavily affected by the subprime mortgage crisis in 2008. GSE also have the highest volatility of return, as exhibit in the kurtosis >3 in all periods, which is leptokurtic and in line with the highest standard deviation compared to other sample groups.

Table 6.2. Summary Statistics of Daily Returns in Group

2017–2019	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0002	0.0101	-0.0525	0.0445	0.0005	-0.7604	3.7225
Commercial Banks	0.0005	0.0127	-0.0491	0.0501	-0.0001	-0.1704	1.8954
Insurance Companies	0.0003	0.0105	-0.0507	0.0455	0.0002	-0.4323	2.6957
Govt Support Entities	0.0005	0.0401	-0.2255	0.4280	-0.0028	2.2306	25.8118
2014–2016	**Mean**	**SD**	**Min**	**Max**	**Median**	**Skewness**	**Kurtosis**
Investment Banks	0.0003	0.0110	-0.0646	0.0443	0.0008	-0.2746	2.8256
Commercial Banks	0.0005	0.0143	-0.0819	0.0661	0.0009	-0.2163	3.0495
Insurance Companies	0.0003	0.0115	-0.0638	0.0421	0.0008	-0.3833	2.5397
Govt Support Entities	0.0014	0.0473	-0.3715	0.4574	-0.0029	1.3449	22.5235
2011–2013	**Mean**	**SD**	**Min**	**Max**	**Median**	**Skewness**	**Kurtosis**
Investment Banks	0.0006	0.0156	-0.0864	0.0742	0.0006	-0.0992	4.3880
Commercial Banks	0.0005	0.0213	-0.1333	0.1074	0.0006	-0.1316	4.8545
Insurance Companies	0.0007	0.0145	-0.0956	0.0689	0.0004	-0.2353	5.2592
Govt Support Entities	0.0052	0.0681	-0.3952	0.5237	-0.0029	1.2806	12.1369
2008–2010	**Mean**	**SD**	**Min**	**Max**	**Median**	**Skewness**	**Kurtosis**
Investment Banks	0.0003	0.0385	-0.1545	0.1967	0.0001	0.5077	5.9724
Commercial Banks	-0.0005	0.0471	-0.2775	0.3320	-0.0012	0.9729	10.5597
Insurance Companies	0.0007	0.0390	-0.1739	0.2072	-0.0001	0.6611	5.8978
Govt Support Entities	-0.0003	0.0997	-0.8619	0.8995	-0.0100	1.3043	20.8201

2005–2007	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0004	0.0084	-0.0408	0.0452	0.0004	0.0963	4.0320
Commercial Banks	0.0003	0.0126	-0.0565	0.0662	0.0004	-0.0319	4.6492
Insurance Companies	0.0002	0.0105	-0.0650	0.0553	0.0000	-0.1286	6.1507
Govt Support Entities	-0.0006	0.0211	-0.2676	0.1873	-0.0005	-1.4853	43.2596

2002–2004	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0004	0.0117	-0.0477	0.0756	0.0003	0.6283	5.2414
Commercial Banks	0.0004	0.0172	-0.0831	0.0903	-0.0002	0.3658	3.2758
Insurance Companies	0.0005	0.0155	-0.0626	0.0630	0.0004	0.1124	2.7498
Govt Support Entities	0.0001	0.0153	-0.1045	0.0768	0.0002	-0.2635	4.5743

The results of investigating individual entities' returns confirm the group data. As shown in Table 6.3, the FMCC and FNMA returns are more volatile with extreme tail, as represent in the kurtosis value. From this table, we also note that during the global financial crises, as exhibited in the 2008–2010 window, shareholders took the hit and suffered losses, with the minimum negative value being much lower and the maximum also tending to be higher compared to other periods. Individual returns for LEH are calculated up to their last trading day in September 2008. The negative skewness returns of normal distribution and its complete loss (appearing as –1 minimum value) speak for the condition of the company as it neared bankruptcy.

Further, for the preliminary perspective of correlation existence in the US capital market, we run pairwise returns correlation test, with the results displayed in Table 6.4. The results for all entities are significant at the 5% confidence level. This confirms our research assumption of interconnectedness and co-movement among the sample. Indication of co-movement of stock return results warrants deeper investigation. For insight, we also run simple linear regression for all samples using the benchmark index SP 500 as the dependent variable. Although this did not explicitly show interconnectedness among the sample, it provided a different perspective of direction (see robustness test 1 at the end of this chapter).

Table 6.3. Summary Statistics of Daily Returns: All Samples

	SP500	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA
2002–2004																					
Mean	0.000	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.000
SD	0.012	0.020	0.013	0.011	0.017	0.016	0.014	0.020	0.017	0.024	0.019	0.022	0.019	0.020	0.033	0.017	0.019	0.016	0.012	0.016	0.016
Min	-0.038	-0.104	-0.069	-0.057	-0.072	-0.083	-0.101	-0.157	-0.065	-0.181	-0.068	-0.110	-0.085	-0.155	-0.398	-0.148	-0.114	-0.086	-0.040	-0.161	-0.069
Max	0.057	0.098	0.061	0.073	0.110	0.080	0.083	0.126	0.072	0.160	0.085	0.080	0.110	0.094	0.128	0.076	0.079	0.068	0.066	0.066	0.095
Median	0.000	-0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000
Skewness	0.350	0.218	0.347	0.677	0.456	0.065	-0.597	-0.092	0.275	0.311	0.384	0.114	0.428	-0.322	-2.534	-1.213	-0.207	-0.116	0.378	-1.134	0.224
Kurtosis	2.247	4.181	2.794	5.862	4.508	2.980	6.772	9.345	1.425	9.415	1.562	1.814	3.855	6.942	30.334	12.240	3.757	2.906	2.802	12.852	3.307
2005–2007																					
Mean	0.000	0.000	0.000	0.001	0.001	0.001	0.000	-0.001	0.001	0.000	0.001	0.000	0.000	0.001	-0.001	0.000	0.001	0.000	0.000	-0.001	0.000
SD	0.008	0.013	0.011	0.008	0.014	0.013	0.010	0.013	0.016	0.012	0.019	0.017	0.013	0.014	0.017	0.012	0.015	0.010	0.011	0.021	0.023
Min	-0.035	-0.080	-0.060	-0.046	-0.068	-0.059	-0.053	-0.081	-0.067	-0.057	-0.077	-0.081	-0.056	-0.053	-0.156	-0.051	-0.075	-0.044	-0.066	-0.287	-0.248
Max	0.029	0.060	0.055	0.042	0.121	0.066	0.052	0.069	0.085	0.063	0.100	0.074	0.064	0.120	0.090	0.066	0.085	0.064	0.062	0.188	0.186
Median	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	-0.001
Skewness	-0.316	-0.245	0.074	0.177	0.930	0.240	-0.125	-0.384	0.080	0.360	0.163	-0.228	0.069	1.086	-0.906	0.451	0.393	0.665	0.095	-1.711	-0.939
Kurtosis	2.404	7.133	5.035	4.431	10.163	2.982	4.380	7.729	2.693	4.155	3.144	3.400	3.503	10.470	12.211	4.145	5.093	6.397	6.925	53.000	26.580
2008–2010																					
Mean	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.001	-0.022	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.000
SD	0.019	0.083	0.035	0.021	0.049	0.055	0.058	0.062	0.037	0.043	0.131	0.059	0.039	0.041	0.051	0.045	0.050	0.039	0.049	0.107	0.100
Min	-0.090	-0.608	-0.212	-0.121	-0.268	-0.247	-0.262	-0.390	-0.167	-0.179	-1.000	-0.259	-0.176	-0.272	-0.250	-0.261	-0.419	-0.182	-0.190	-0.827	-0.896
Max	0.116	0.660	0.217	0.161	0.280	0.383	0.353	0.578	0.265	0.251	0.464	0.870	0.206	0.248	0.264	0.371	0.313	0.228	0.328	1.284	0.706
Median	0.001	-0.002	0.000	-0.001	-0.001	0.001	-0.001	-0.001	-0.001	-0.001	-0.010	-0.001	0.001	-0.001	0.000	0.000	-0.001	0.000	-0.001	-0.009	-0.010
Skewness	0.093	0.903	0.092	1.339	0.516	0.886	0.846	1.161	1.170	0.976	-4.141	4.412	0.501	0.695	0.384	1.156	-0.126	0.601	1.492	2.650	0.892
Kurtosis	6.413	17.154	10.656	14.197	8.397	9.220	8.024	16.434	10.249	6.614	30.509	66.319	4.650	8.578	4.952	11.510	14.391	6.167	9.436	35.317	17.680
2011–2013																					
Mean	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.000	0.001		0.001	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.005	0.005
SD	0.010	0.022	0.014	0.012	0.021	0.020	0.026	0.024	0.019	0.019		0.027	0.014	0.018	0.018	0.016	0.017	0.015	0.017	0.069	0.069
Min	-0.067	-0.100	-0.065	-0.061	-0.099	-0.108	-0.203	-0.164	-0.101	-0.094		-0.145	-0.088	-0.097	-0.121	-0.082	-0.101	-0.090	-0.090	-0.387	-0.403
Max	0.047	0.103	0.076	0.081	0.089	0.092	0.167	0.138	0.095	0.084		0.166	0.071	0.076	0.085	0.067	0.107	0.082	0.081	0.543	0.504
Median	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000		0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	-0.002
Skewness	-0.474	-0.088	0.283	0.724	-0.158	-0.223	-0.073	-0.196	-0.021	0.002		0.224	-0.226	-0.098	-0.068	-0.120	0.075	-0.180	-0.121	1.305	1.203
Kurtosis	5.542	2.820	4.191	8.154	2.541	4.104	8.257	5.491	3.600	3.721		5.037	3.895	3.257	4.835	3.449	5.307	6.111	4.415	12.195	11.415
2014–2016																					
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001		0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.001

	SP500	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA
SD	0.008	0.012	0.010	0.009	0.016	0.016	0.017	0.016	0.014	0.013		0.017	0.013	0.014	0.015	0.012	0.016	0.011	0.012	0.047	0.048
Min	-0.039	-0.073	-0.101	-0.041	-0.107	-0.095	-0.074	-0.094	-0.071	-0.069		-0.102	-0.121	-0.085	-0.131	-0.064	-0.088	-0.056	-0.050	-0.375	-0.368
Max	0.039	0.073	0.057	0.032	0.071	0.064	0.071	0.073	0.059	0.083		0.071	0.090	0.046	0.082	0.048	0.093	0.044	0.076	0.457	0.458
Median	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000		0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.000	-0.003	-0.003
Skewness	-0.338	-0.012	-1.065	0.077	-0.600	-0.369	-0.135	-0.272	-0.275	0.086		-0.236	-0.891	-0.536	-0.864	-0.244	-0.384	-0.318	0.268	1.256	1.413
Kurtosis	2.401	4.218	14.870	1.875	5.143	3.225	2.362	3.805	1.868	3.954		3.338	13.145	3.533	10.127	2.136	4.854	2.373	3.502	21.889	22.582
2017–2019																					
Mean	0.001	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.001		0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
SD	0.008	0.013	0.011	0.010	0.013	0.014	0.014	0.014	0.014	0.012		0.015	0.011	0.013	0.014	0.012	0.015	0.010	0.013	0.040	0.041
Min	-0.041	-0.090	-0.070	-0.060	-0.086	-0.101	-0.059	-0.053	-0.075	-0.048		-0.056	-0.056	-0.095	-0.064	-0.056	-0.085	-0.043	-0.092	-0.235	-0.231
Max	0.050	0.068	0.055	0.051	0.051	0.049	0.072	0.052	0.095	0.047		0.062	0.076	0.057	0.086	0.047	0.090	0.041	0.046	0.428	0.428
Median	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000		0.000	0.001	0.001	0.000	0.001	0.000	0.001	0.000	-0.003	-0.003
Skewness	-0.604	-0.813	-0.607	-0.415	-0.717	-1.010	-0.094	-0.087	-0.033	0.015		-0.049	0.056	-0.801	-0.068	-0.553	-0.213	-0.376	-0.535	2.103	2.250
Kurtosis	5.875	7.826	6.826	6.598	4.064	5.424	2.809	1.656	4.202	1.955		1.657	5.585	6.011	3.828	2.254	4.646	2.230	4.197	25.856	23.883

Table 6.4. Pairwise Returns Correlation at 5% Confidence Level

	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA
AIG	1																			
ALL	0.4138*	1																		
	0.0000																			
BRK	0.3093*	0.5070*	1																	
	0.0000	0.0000																		
MET	0.4742*	0.6834*	0.4581*	1																
	0.0000	0.0000	0.0000																	
PRU	0.4495*	0.6974*	0.5025*	0.7988*	1															
	0.0000	0.0000	0.0000	0.0000																
BAC	0.5232*	0.5847*	0.4866*	0.6667*	0.6894*	1														
	0.0000	0.0000	0.0000	0.0000	0.0000															
C	0.5735*	0.5506*	0.4404*	0.6582*	0.6536*	0.7987*	1													
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000														
GS	0.4100*	0.5796*	0.4819*	0.6175*	0.6421*	0.6759*	0.6769*	1												
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000													
JPM	0.4760*	0.5930*	0.5001*	0.6576*	0.6483*	0.7849*	0.7414*	0.7316*	1											
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000												
LEH	0.7069*	0.3048*	0.0683*	0.3070*	0.3484*	0.4657*	0.5081*	0.5807*	0.3869*	1										
	0.0000	0.0000	0.0043	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000											
MS	0.4426*	0.6019*	0.4554*	0.6286*	0.6671*	0.6540*	0.6569*	0.8080*	0.6629*	0.6092*	1									
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000										
AXP	0.4595*	0.5919*	0.4807*	0.6394*	0.6568*	0.6675*	0.6240*	0.6517*	0.6992*	0.4370*	0.6423*	1								
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000									
BK	0.4467*	0.5806*	0.4411*	0.6489*	0.6371*	0.6874*	0.6641*	0.6885*	0.7317*	0.4117*	0.6798*	0.6621*	1							
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000								
COF	0.3913*	0.5544*	0.4038*	0.6026*	0.6362*	0.6512*	0.5934*	0.5858*	0.6683*	0.3134*	0.5626*	0.7026*	0.6254*	1						
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000							
PNC	0.4183*	0.5499*	0.4531*	0.6598*	0.6518*	0.7536*	0.6646*	0.6138*	0.7802*	0.3275*	0.5770*	0.6551*	0.6795*	0.6307*	1					
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000						
STT	0.3909*	0.5492*	0.4313*	0.6361*	0.6437*	0.6504*	0.6048*	0.6579*	0.6916*	0.3748*	0.6189*	0.6174*	0.7504*	0.6020*	0.6933*	1				
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000					
USB	0.4506*	0.5993*	0.4538*	0.6585*	0.6494*	0.7594*	0.6571*	0.6156*	0.7690*	0.3465*	0.5747*	0.6811*	0.6784*	0.6608*	0.7726*	0.6451*	1			
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000				
WFC	0.4590*	0.5938*	0.4585*	0.6684*	0.6888*	0.8184*	0.7169*	0.6460*	0.7836*	0.3646*	0.6035*	0.6908*	0.6927*	0.6690*	0.7972*	0.6826*	0.8167*	1		
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
FMCC	0.3149*	0.1906*	0.1413*	0.2195*	0.2104*	0.2822*	0.3016*	0.2471*	0.2502*	0.4741*	0.2350*	0.2337*	0.2100*	0.2124*	0.2213*	0.1952*	0.2279*	0.2470*	1	
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
FNMA	0.2960*	0.2064*	0.1572*	0.2336*	0.2247*	0.2910*	0.3025*	0.2599*	0.2599*	0.3730*	0.2306*	0.2471*	0.2115*	0.2189*	0.2232*	0.2019*	0.2323*	0.2567*	0.8986*	1
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	

6.4.2 Empirical Analysis

6.4.2.1 PCA

As discussed in Section 6.3, if, using a small number of institutions, PCA can explain the volatility within the market, then the system is highly interconnected, stated in the condition $h_n > H$. To assess the time variation of h_n, we could detect accumulation of interconnectedness or correlation and integration that contributes to systemic risk (Bisias et al. 2012). The cumulative risk fraction represented by eigenvalues are exhibited in Table 6.5. We note that during the global financial crises in 2008, cumulative risk is the highest at score 93.49% with eigenvalue 5.14. Another interesting point is the higher PC 1-3 during the subprime mortgage crisis in 2008–2009, European debt crisis in 2010–2011, Russian ruble crisis in 2014–2015 and stock market selloff in 2015–2016 compared to pre-crisis. As per theory, the PCA is always efficient across the first three planes (or dimensions) and then become less efficient from the fourth component and higher. Our results confirm theory where the first three are well represented, as PC 1-3 captures a significant portion of the variance. The results are consistent when we examine PC 1-10. Our result of principal component capturing and explaining the majority of variance within the sample periods is consistent with Billio et al. (2012).

Table 6.5. Cumulative Risk and Eigenvalue during the Period 2002–2019

Cumulative Risk Fraction (First 10) and Eigenvalue (First 3)					
Investment Banks, Commercial Banks, Insurance Companies, Govt. Support Entities					
Sample Period	PC 1	PC 1-3	PC 1-5	PC 1-10	Eigenvalue λ_k
2017–2019	60.02%	74.53%	81.23%	92.04%	4.720
2014–2016	65.88%	79.49%	85.22%	93.97%	5.034
2011–2013	65.77%	79.37%	84.51%	93.05%	5.027
2008–2010	61.10%	77.09%	84.31%	93.49%	5.139
2005–2007	55.34%	66.07%	73.57%	86.81%	4.404
2002–2004	56.94%	68.15%	75.97%	87.74%	4.544

Referring to Figure 6.1 for eigenvalue λ_k, we can spot the same direction as displayed in Table 6.5. The higher PC 1-3 portion shows that intercorrelated exposures within the sample become higher and more persistent. The highest linkage was during crises, as dated in our sample windows. Additionally, the same patterns direction along the curve PC 1–PC 3 reflect the co-movement return in the sample. When the sample is deconstructed into groups, it is clear that investment and commercial banks dominate the US financial capital market during all periods. The figures are the same pre- and post-2008 (see Table 6.6). Identification of the dominance of banks using PCA methodology to capture covariance movement aligns with

Baek, Cursio and Cha (2015). Each entity is significant in the US financial market, as shown in Figure 6.2 using two dimensions of component loading. Stata calculation shows changes across periods; prior to the crises, the companies have some distance between each other (i.e., not much overlapping exposure between groups of industries). Consequently, during the 2008 global financial crises, FMCC, FNMA, LEH and AIG have weak contribution to systematic risk. As we know, these companies were badly affected by the crises. After the crises, there is a tendency of interlinkages between US financial firms. The investment and commercial banks stay in groups, while the insurance companies and government support entities group together. Based on the same figures for the most recent period of 2017–2019, regulators also should pay attention to large contributors to systematic risk, such as JPM, MS, BAC, C, GS, BK and WFC. The appearance of these companies in our results is in line with the 2019 G-SIBs list issued by FSB (2019).

Figure 6.1. Principal Component Explained Variance

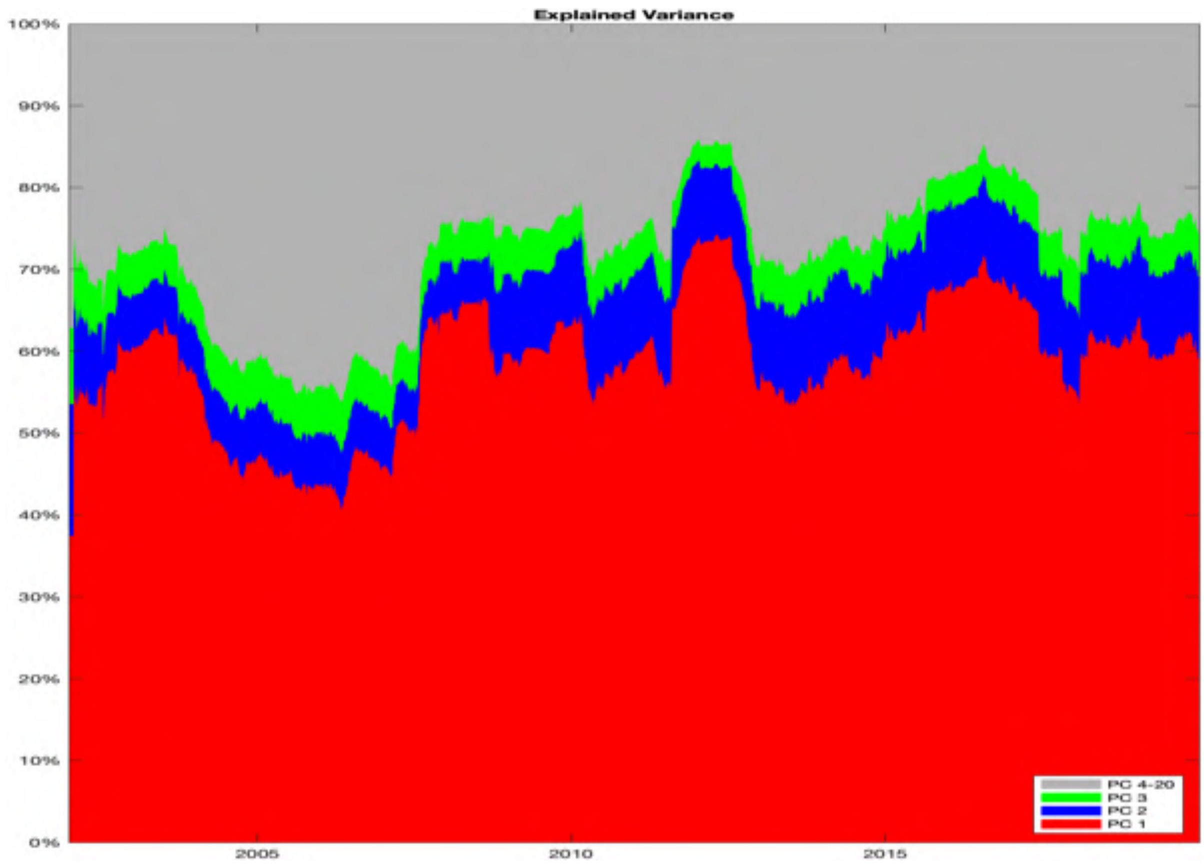
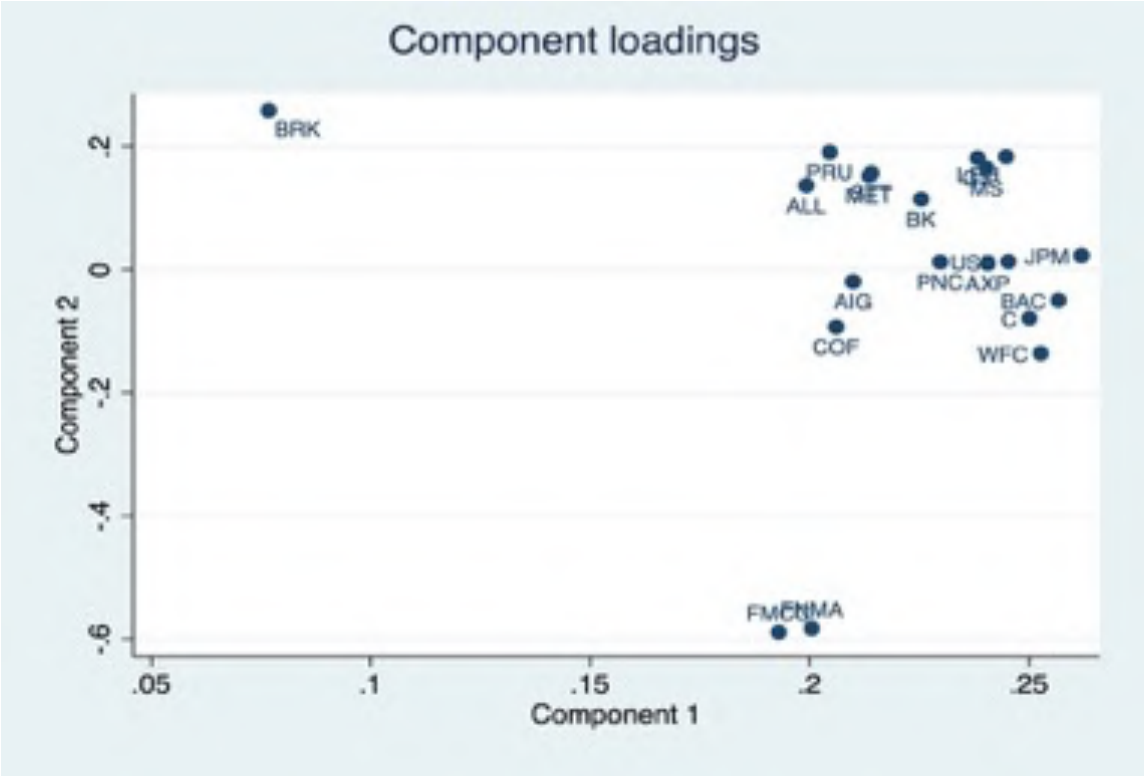


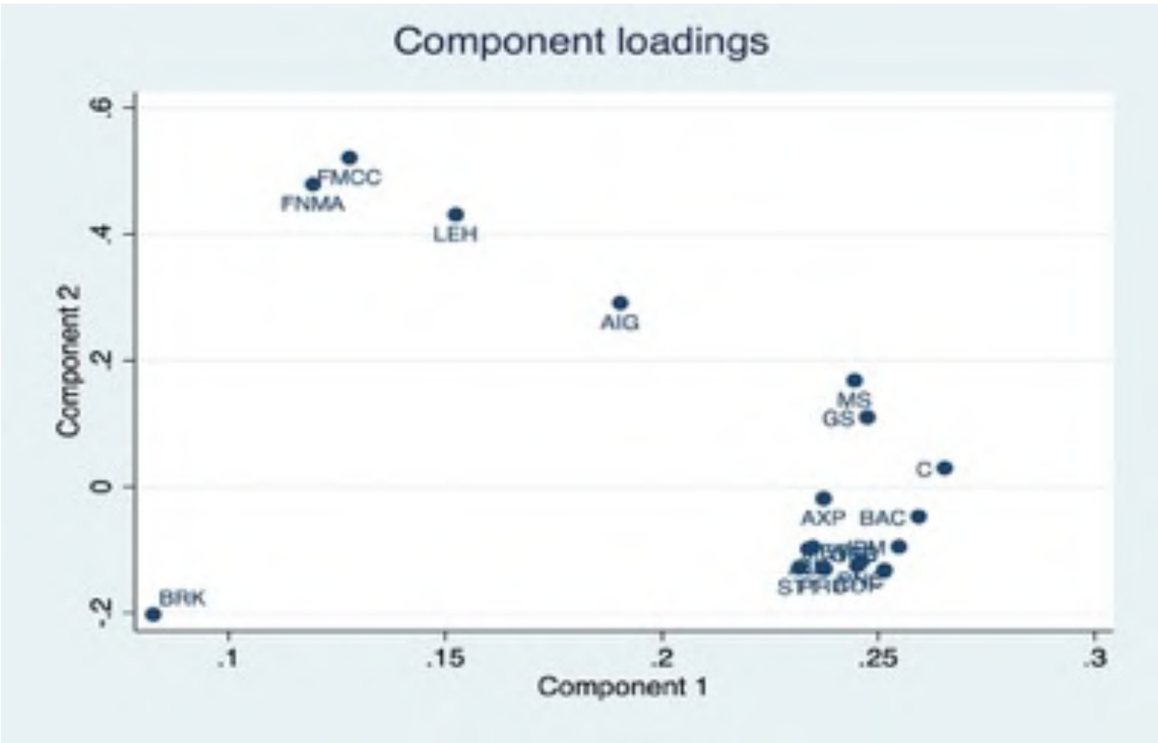
Table 6.6. PCA Statistics for All Samples

	2017–2019					2008–2010				
	PC 1	PC 1-3	PC 1-5	PC 1-10	PC 1-20	PC 1	PC 1-3	PC 1-5	PC 1-10	PC 1-20
Investment Banks										
Mean	0.264	0.023	-0.024	-0.035	-0.021	0.237	0.076	0.062	-0.005	-0.018
Min	0.250	-0.219	-0.219	-0.467	-0.772	0.152	-0.433	-0.433	-0.462	-0.641
Max	0.272	0.272	0.272	0.272	0.632	0.265	0.431	0.431	0.431	0.431
Commercial Banks										
Mean	0.238	0.046	0.058	0.064	0.039	0.243	0.061	0.042	0.020	0.022
Min	0.222	-0.153	-0.263	-0.491	-0.592	0.232	-0.170	-0.190	-0.614	-0.614
Max	0.258	0.258	0.545	0.675	0.675	0.251	0.251	0.436	0.504	0.504
Insurances										
Mean	0.209	0.198	0.122	0.053	0.035	0.196	0.033	0.019	0.057	0.039
Min	0.179	-0.029	-0.465	-0.524	-0.526	0.083	-0.356	-0.484	-0.513	-0.513
Max	0.244	0.584	0.584	0.584	0.584	0.238	0.291	0.906	0.906	0.906
Govt. Support Ent.										
Mean	0.063	0.247	0.155	0.074	0.042	0.124	0.356	0.214	0.134	0.066
Min	0.060	-0.028	-0.028	-0.028	-0.707	0.119	0.119	-0.041	-0.055	-0.498
Max	0.066	0.704	0.704	0.704	0.705	0.128	0.521	0.521	0.521	0.521
	2014–2016					2005–2007				
Investment Banks										
Mean	0.257	0.040	0.001	-0.015	-0.007	0.249	0.085	0.024	-0.003	-0.009
Min	0.253	-0.233	-0.233	-0.457	-0.591	0.238	-0.147	-0.271	-0.271	-0.626
Max	0.262	0.262	0.262	0.262	0.568	0.262	0.262	0.320	0.320	0.566
Commercial Banks										
Mean	0.237	0.058	0.036	0.031	0.014	0.231	0.064	0.013	0.010	0.012
Min	0.182	-0.112	-0.294	-0.491	-0.491	0.206	-0.136	-0.301	-0.535	-0.788
Max	0.257	0.257	0.908	0.908	0.908	0.253	0.253	0.253	0.842	0.842
Insurances										
Mean	0.220	0.162	0.124	0.056	0.046	0.181	0.186	0.166	0.098	0.052
Min	0.178	-0.149	-0.149	-0.720	-0.720	0.077	-0.045	-0.254	-0.711	-0.711
Max	0.245	0.809	0.809	0.809	0.809	0.214	0.904	0.904	0.904	0.904
Govt. Support Ent.										
Mean	0.081	0.268	0.164	0.085	0.042	0.197	-0.090	0.017	0.026	0.011
Min	0.080	0.022	-0.002	-0.016	-0.706	0.193	-0.589	-0.589	-0.589	-0.647
Max	0.081	0.701	0.701	0.701	0.706	0.201	0.201	0.302	0.302	0.639
	2011–2013					2002–2004				
Investment Banks										
Mean	0.248	-0.032	0.011	0.008	0.006	0.249	0.029	0.019	-0.039	-0.016
Min	0.241	-0.421	-0.421	-0.421	-0.652	0.241	-0.151	-0.297	-0.424	-0.659
Max	0.256	0.256	0.275	0.275	0.543	0.257	0.257	0.257	0.257	0.719
Commercial Banks										
Mean	0.241	0.133	0.065	0.028	0.014	0.230	0.019	0.036	0.060	0.023
Min	0.222	-0.037	-0.417	-0.609	-0.694	0.187	-0.239	-0.466	-0.466	-0.619
Max	0.254	0.374	0.501	0.501	0.741	0.252	0.252	0.358	0.724	0.724
Insurances										
Mean	0.233	0.114	0.064	0.044	0.030	0.188	0.156	0.057	0.045	0.031
Min	0.222	-0.042	-0.482	-0.482	-0.482	0.094	-0.326	-0.401	-0.409	-0.569
Max	0.250	0.250	0.752	0.752	0.752	0.236	0.650	0.650	0.759	0.759
Govt. Support Ent.										
Mean	0.047	0.250	0.149	0.073	0.038	0.178	0.311	0.227	0.108	0.057
Min	0.046	-0.007	-0.016	-0.024	-0.706	0.174	0.114	-0.053	-0.069	-0.529
Max	0.048	0.705	0.705	0.705	0.705	0.182	0.634	0.634	0.634	0.634

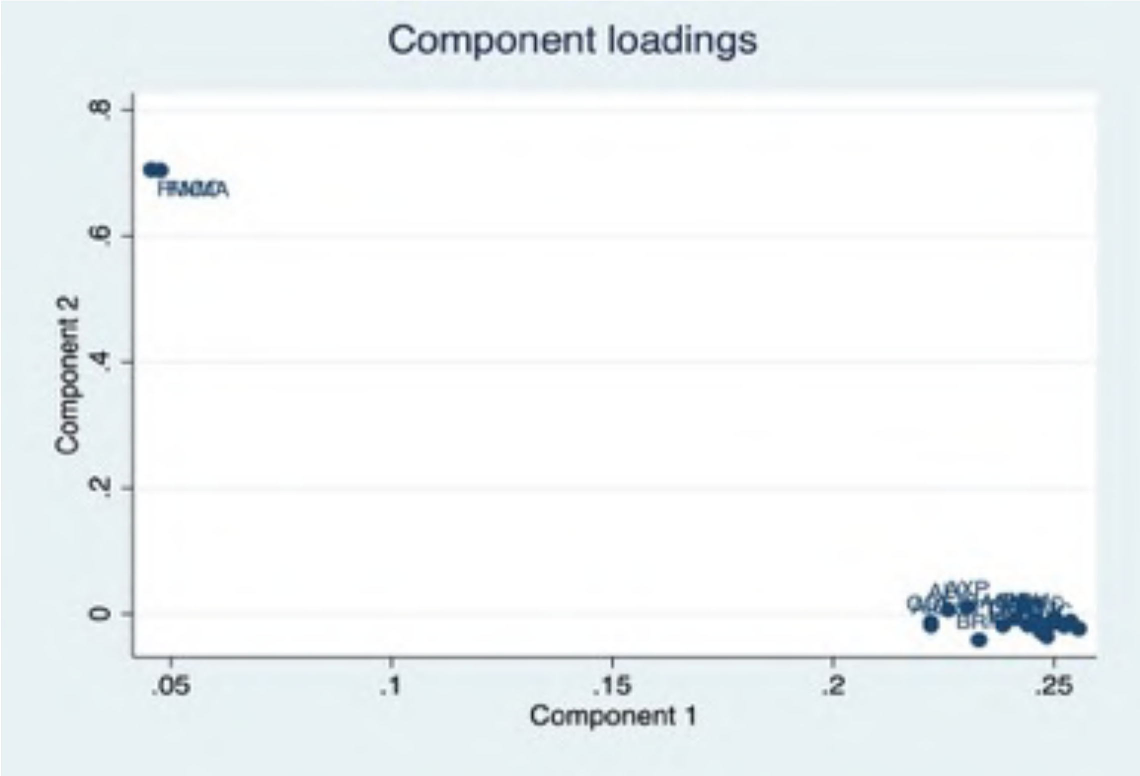
Figure 6.2. Two Dimension Component Loading



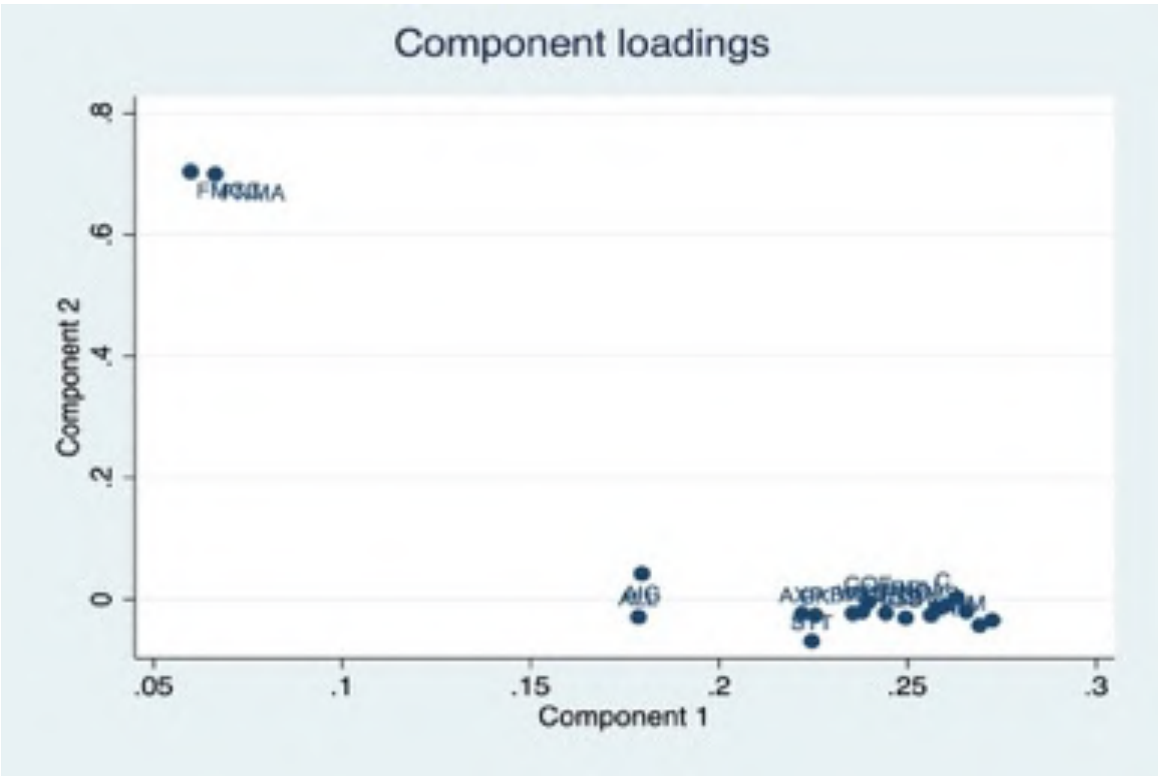
(A) Pre-crises: 2005–2007



(B) Crises: 2008–2010



(C) Post-crises: 2011–2013



(D) Current: 2017–2019

6.4.2.2 Granger Causality

Granger causality has been used to identify correlated exposure and interconnectedness of financial institutions in prior studies (Balboa, López-Espinosa & Rubia 2015; Billio et al. 2012; Mazzarisi et al. 2020). The outputs of several centrality measures, presented in Table 6.7 and Figure 6.3, provide important information:

a. *Degree centrality*—the number of edges point to a node, that is, an institution via which many banks conduct transactions. Based on analysis of the full sample window, FMCC is the key institution in the US financial system in terms of network adjacency, followed by BRK, PRU, JPM and GS. These institutions likely also facilitate other banks' financial transaction needs, such as mortgage, risk transfer insurance, investment, billing payment, etc. During the 2008 global financial crises, the list was led by C, MET, JPM, PRU and BRK.

b. *Closeness centrality*—the average shortest edges built on all observation periods to reach nodes interconnectedness is through FMCC, STT, C, BK and JPM. This is the most vital information in terms of contribution to systematic risk. However, this list is quite volatile, likely due to dynamic transactions that keep the financial market rolling. During times of crises, C, MET, ALL, JPM and PRU have extensive networks in the system.

c. *Eigenvector centrality*—translated as not only how many edges but also how many really count or matter. The key players in the US financial system are once again C, FMCC, STT, BAC and BK. At the time of the global financial crises, the key players were C, ALL, MET, PRU and JPM.

Table 6.7. Centrality Value of All Samples

Firms	Closeness Centrality		Degree Centrality		Eigenvector Centrality	
	Full	Crises	Full	Crises	Full	Crises
AIG	0.655	0.655	0.947	0.789	0.053	0.086
ALL	0.633	0.792	0.579	0.789	0.047	0.128
BRK	0.655	0.576	1.421	0.842	0.052	0.064
MET	0.613	0.792	0.737	1.105	0.045	0.111
PRU	0.576	0.760	1.211	0.842	0.040	0.097
BAC	0.704	0.633	0.789	0.684	0.063	0.079
C	0.792	0.905	1.053	1.316	0.077	0.155
GS	0.543	0.000	1.158	0.789	0.031	0.000
JPM	0.704	0.760	1.158	0.947	0.060	0.092
LEH	0.463	0.000	0.211	0.474	0.009	0.000
MS	0.633	0.339	1.000	0.579	0.045	0.003
AXP	0.679	0.404	0.947	0.368	0.062	0.012
BK	0.760	0.422	0.895	0.316	0.063	0.015
COF	0.528	0.388	1.053	0.632	0.021	0.012
PNC	0.633	0.559	1.105	0.737	0.049	0.034
STT	0.792	0.000	0.947	0.368	0.075	0.000
USB	0.655	0.576	1.053	0.526	0.049	0.041

Firms	Closeness Centrality		Degree Centrality		Eigenvector Centrality	
	Full	Crises	Full	Crises	Full	Crises
WFC	0.543	0.633	1.053	0.684	0.030	0.052
FMCC	0.792	0.422	1.526	0.737	0.075	0.016
FNMA	0.679	0.302	1.053	0.684	0.055	0.003

Based on centrality measures for the full sample window, US policymakers should monitor FMCC (government support entity); PRU and STT (insurance companies); and C, JPM, BAC and BK (banks). The importance of these firms' connections—that is, posed systematic risk—is highlighted in Figure 6.4.

6.4.2.3 Variance Decomposition

To map the risk direction of systemic failure in the US financial market, we used Diebold and Yılmaz's (2014) model. Application of their model provides a different perspective of spillover risk between entities in the system. The model is based on pairwise direction connectedness from j to i $C^H_{i \leftarrow j} = d^H_{ij}$, where $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i}1$. Net pairwise $\frac{N^2-N}{2}$ is analogous to bilateral interbank balances. As shown in Table 6.8, total directional connectedness from others to i is defined as $C^H_{i \leftarrow \circ} = \sum_{j=1}^{N} d^H_{ij} \quad j \neq i$, and the opposite of total directional connectedness to others from j as $C^H_{\circ \leftarrow j} = \sum_{i=1}^{N} d^H_{ij} \quad i \neq j$. The grand total off-diagonal entries, equivalent of the sum 'from' and 'to' measures of total connectedness, is $C^H = \frac{1}{N} \sum_{i,j=1}^{N} d^H_{ij} \quad i \neq j$.

Table 6.8. Pairwise Direction Connectedness

	X_1	X_2	⋯	X_N	From others
X_1	d^H_{11}	d^H_{12}	⋯	d^H_{1N}	$\sum_{j=1}^{N} d^H_{1j},\ j \neq 1$
X_2	d^H_{21}	d^H_{22}	⋯	d^H_{2N}	$\sum_{j=1}^{N} d^H_{2j},\ j \neq 2$
⋮	⋮	⋮	⋱	⋮	⋮
X_N	d^H_{N1}	d^H_{N2}	⋯	d^H_{NN}	$\sum_{j=1}^{N} d^H_{Nj},\ j \neq N$
To others	$\sum_{i=1}^{N} d^H_{i1}$ $i \neq 1$	$\sum_{i=2}^{N} d^H_{i1}$ $i \neq 2$	⋯	$\sum_{i=1}^{N} d^H_{iN}$ $i \neq N$	$\frac{1}{N} \sum_{i,j=1}^{N} d^H_{ij}$ $i \neq j$

The results, shown in Table 6.9, show that net position is mostly zero, which reflects the accuracy of calculation with some excess of error. During the 2008 global financial crises, the banking groups are dominant or absorb many interlinkages (both liabilities and assets) from other financial market participants. This outcome stresses the importance of the banking sector to the US financial market over the sample period. The results also indicate a higher spillover early in the early global financial crises (17.40) compared to other times of the crises. The highest individual entities' variance spillover are for BAC, JPM, COF, WFC, C and GS. The appearance of C and JPM in this list is consistent with the Granger analysis results presented in Section 6.4.2.2. Note that although some insurance companies like ALL, MET and PRU are repeatedly listed as systemically important institutions based on Granger methodology, their pairwise directional connectedness is still below that of the sampled banking entities. An explanation for this could be that these insurance entities may have a wide network, but the banks still have a larger portfolio in terms of assets in custodian and equity. The outcome indicates that regulators must validate and calibrate any measure of systemically important institutions' risk exposure and systematic risk, and that such measurements must consider multiple, complementary factors.

An alternative way to model interconnectedness in the financial system and the interlinkage of transactions is to use detailed balance sheet data using Gai and Kapadia's (2010) model (see robustness test 2 at the end of this chapter). Using this model, we can more clearly map the source and risk direction of interlinkage exposures among institutions, including the weight of hit and how much hit one or some entities could sustain based on their equity. However, despite its advantages, this model requires extensive interlinkage assets and liabilities statistics—information to which only the bank supervisors and policymakers are privy. The next chapter undertakes analyses using the market models of CoVaR, MES and SRISK.

Figure 6.3. Centrality Measures

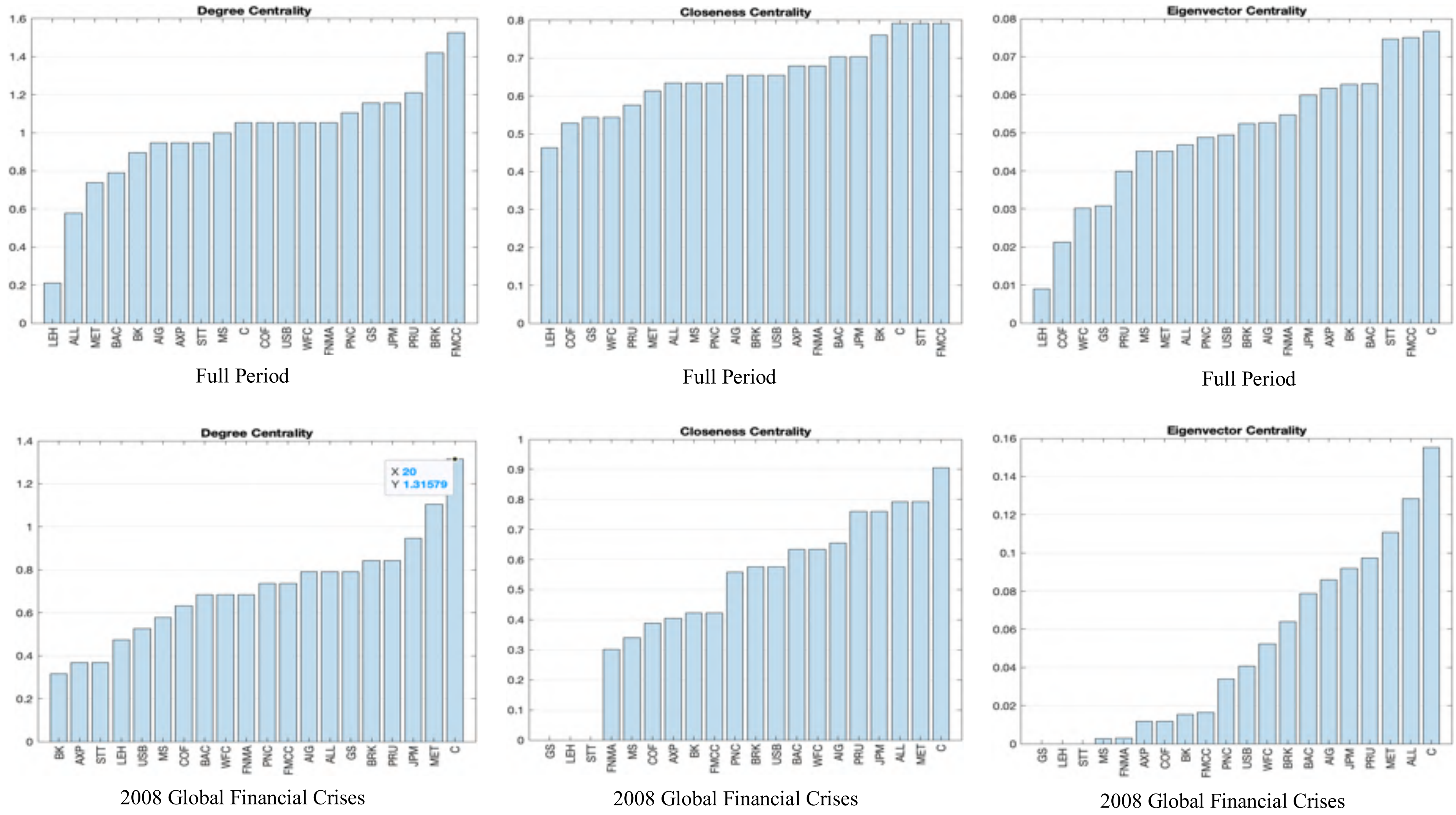
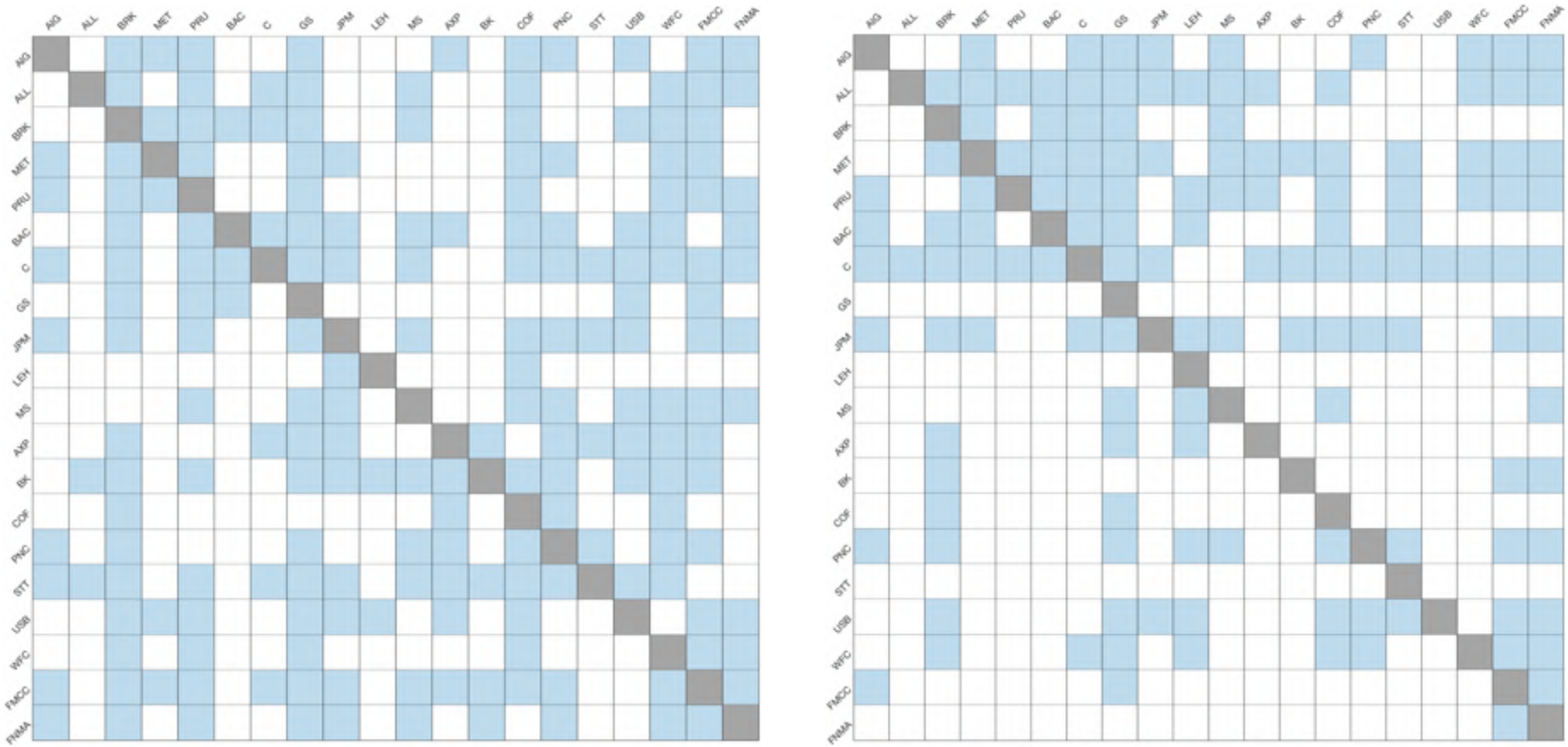


Figure 6.4. Network Matrix Adjacency



(A) Full Period   (B) 2008 Global Financial Crises

Table 6.9. Risk Spillover

TO	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA	TOTAL
2002	0.97	0.67	0.16	0.66	0.67	1.09	1.10	0.96	0.94	1.04	1.09	1.04	0.93	0.45	1.01	1.17	0.88	0.90	0.62	0.65	16.99
2003	0.92	0.54	0.18	0.86	0.91	0.67	1.15	1.06	1.20	0.98	1.09	1.06	1.01	0.67	0.90	0.70	0.96	0.96	0.45	0.64	16.91
2004	0.65	0.65	0.22	0.71	0.80	0.87	1.06	1.01	1.04	0.88	0.91	0.80	0.83	0.76	0.94	0.65	0.74	0.92	0.68	0.56	15.66
2005	0.42	0.58	0.05	0.50	0.53	1.08	0.92	0.79	1.12	0.85	0.64	0.76	0.98	0.45	0.92	0.75	1.02	1.09	0.69	0.59	14.72
2006	0.79	0.52	0.08	0.78	0.58	0.93	0.89	0.90	1.19	0.99	0.96	0.96	0.56	0.47	0.56	0.94	0.84	0.92	0.62	0.90	15.38
2007	0.90	0.66	0.16	0.89	0.85	1.13	1.02	0.97	1.11	1.06	0.92	0.99	1.00	0.83	0.95	0.73	1.06	1.04	0.53	0.61	17.40
2008	0.73	0.78	0.43	0.72	0.85	1.16	1.00	1.00	1.06		0.90	0.97	0.95	1.11	0.97	0.90	1.11	1.10	0.45	0.42	16.60
2009	0.35	0.80	0.57	1.06	1.01	1.07	0.82	0.96	1.09		0.91	0.93	0.96	0.81	0.99	0.91	0.97	1.09	0.49	0.59	16.38
2010	0.45	0.86	0.70	0.94	1.01	1.05	0.80	0.56	1.12		0.89	0.87	0.94	0.89	0.95	0.93	1.08	1.09	0.45	0.42	16.01
2011	0.79	0.85	0.83	1.01	1.02	0.92	1.00	0.90	1.05		0.94	0.89	0.92	0.82	0.99	0.93	0.96	0.96	0.41	0.45	16.66
2012	0.57	0.53	0.65	0.97	0.87	0.99	1.08	1.01	0.85		0.97	0.84	1.03	0.77	0.94	0.79	0.97	1.04	0.46	0.41	15.74
2013	0.76	0.74	0.88	0.91	0.90	0.84	1.01	0.94	0.93		0.99	0.78	1.01	0.68	0.95	0.89	0.71	0.91	0.49	0.49	15.80
2014	0.85	0.61	0.77	1.05	0.98	0.89	0.91	0.94	1.01		0.91	0.93	0.80	0.83	0.99	0.97	1.00	0.91	0.46	0.47	16.29
2015	0.86	0.51	0.82	1.04	1.00	1.02	1.11	1.03	1.11		1.03	0.36	1.03	0.67	1.03	0.94	1.06	1.12	0.43	0.43	16.60
2016	0.87	0.33	0.76	0.87	1.03	1.08	1.12	1.10	1.14		1.10	0.38	0.98	0.91	1.11	0.86	1.08	0.93	0.47	0.44	16.57
2017	0.20	0.34	0.83	0.87	1.02	1.15	1.03	0.93	1.16		1.06	0.68	0.81	0.72	1.15	0.68	1.11	0.85	0.41	0.45	15.47
2018	0.51	0.57	0.89	0.84	1.03	1.08	1.01	0.94	1.13		1.09	0.82	0.84	0.96	0.90	0.76	0.90	0.83	0.43	0.47	16.01
2019	0.52	0.44	0.82	1.03	1.00	1.13	1.13	0.99	1.09		1.12	0.74	0.59	0.88	1.04	0.75	1.07	0.83	0.46	0.45	16.08
																					291.26
FROM	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA	TOTAL
2002	0.88	0.83	0.56	0.83	0.82	0.89	0.89	0.88	0.88	0.89	0.89	0.89	0.88	0.77	0.89	0.90	0.87	0.88	0.82	0.82	16.99
2003	0.87	0.80	0.54	0.87	0.87	0.84	0.89	0.89	0.89	0.88	0.89	0.89	0.88	0.84	0.88	0.84	0.87	0.88	0.77	0.82	16.91
2004	0.75	0.76	0.54	0.78	0.80	0.81	0.84	0.83	0.84	0.82	0.82	0.80	0.80	0.80	0.82	0.76	0.79	0.82	0.76	0.72	15.66
2005	0.65	0.72	0.15	0.68	0.71	0.84	0.82	0.79	0.84	0.79	0.75	0.77	0.82	0.67	0.81	0.78	0.83	0.84	0.76	0.72	14.72
2006	0.79	0.72	0.31	0.79	0.75	0.82	0.82	0.82	0.86	0.84	0.83	0.82	0.73	0.70	0.74	0.82	0.81	0.82	0.76	0.81	15.38
2007	0.88	0.86	0.64	0.89	0.88	0.91	0.90	0.89	0.91	0.90	0.89	0.89	0.90	0.87	0.89	0.86	0.90	0.90	0.81	0.83	17.40
2008	0.84	0.86	0.78	0.86	0.87	0.90	0.89	0.90	0.90		0.88	0.89	0.89	0.90	0.89	0.89	0.90	0.90	0.65	0.63	16.22
2009	0.68	0.87	0.83	0.89	0.89	0.89	0.86	0.89	0.90		0.88	0.88	0.89	0.87	0.89	0.88	0.89	0.90	0.71	0.74	16.24
2010	0.77	0.87	0.85	0.88	0.89	0.89	0.86	0.82	0.89		0.87	0.87	0.88	0.87	0.88	0.87	0.89	0.89	0.56	0.54	15.85
2011	0.90	0.90	0.90	0.91	0.92	0.91	0.92	0.91	0.92		0.91	0.90	0.91	0.90	0.92	0.91	0.91	0.91	0.54	0.57	16.58
2012	0.80	0.79	0.82	0.87	0.86	0.88	0.88	0.88	0.86		0.87	0.85	0.88	0.84	0.87	0.85	0.87	0.88	0.59	0.56	15.70
2013	0.84	0.84	0.86	0.87	0.86	0.86	0.88	0.87	0.87		0.87	0.84	0.88	0.83	0.87	0.86	0.83	0.86	0.54	0.54	15.66
2014	0.87	0.83	0.86	0.89	0.89	0.88	0.88	0.89	0.89		0.88	0.88	0.87	0.87	0.89	0.89	0.89	0.88	0.64	0.65	16.23
2015	0.88	0.82	0.88	0.91	0.90	0.91	0.91	0.91	0.91		0.91	0.77	0.91	0.86	0.91	0.90	0.91	0.91	0.69	0.69	16.49

2016	0.89	0.76	0.87	0.89	0.90	0.91	0.91	0.91	0.91		0.91	0.78	0.90	0.89	0.91	0.89	0.91	0.89	0.70	0.69	16.44
2017	0.58	0.67	0.85	0.86	0.88	0.89	0.88	0.87	0.89		0.88	0.83	0.85	0.83	0.89	0.83	0.88	0.86	0.57	0.59	15.37
2018	0.82	0.83	0.89	0.88	0.90	0.90	0.90	0.89	0.91		0.90	0.88	0.88	0.89	0.89	0.87	0.89	0.88	0.47	0.49	15.95
2019	0.80	0.74	0.86	0.88	0.88	0.90	0.90	0.89	0.89		0.89	0.84	0.82	0.87	0.89	0.85	0.89	0.86	0.62	0.62	15.89
																					289.68

NET	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA	
2002	0.09	-0.17	-0.40	-0.18	-0.15	0.19	0.21	0.08	0.06	0.15	0.19	0.15	0.05	-0.33	0.13	0.27	0.01	0.02	-0.20	-0.17	0.00
2003	0.04	-0.26	-0.36	0.00	0.04	-0.17	0.26	0.17	0.30	0.10	0.20	0.17	0.12	-0.17	0.03	-0.14	0.09	0.08	-0.32	-0.19	0.00
2004	-0.10	-0.11	-0.32	-0.07	0.00	0.06	0.23	0.17	0.20	0.06	0.09	0.00	0.03	-0.03	0.12	-0.11	-0.05	0.10	-0.08	-0.17	0.00
2005	-0.24	-0.14	-0.10	-0.18	-0.18	0.25	0.11	0.00	0.28	0.06	-0.11	-0.01	0.15	-0.22	0.10	-0.03	0.19	0.26	-0.07	-0.13	0.00
2006	-0.01	-0.20	-0.23	-0.01	-0.17	0.10	0.07	0.08	0.33	0.15	0.13	0.13	-0.17	-0.23	-0.18	0.12	0.03	0.10	-0.13	0.09	0.00
2007	0.02	-0.20	-0.48	0.00	-0.02	0.22	0.12	0.07	0.20	0.16	0.03	0.10	0.10	-0.04	0.05	-0.13	0.16	0.14	-0.28	-0.22	0.00
2008	-0.11	-0.09	-0.35	-0.13	-0.02	0.25	0.10	0.11	0.16		0.02	0.08	0.06	0.21	0.08	0.02	0.21	0.19	-0.20	-0.21	0.38
2009	-0.33	-0.07	-0.25	0.17	0.11	0.17	-0.03	0.07	0.19		0.03	0.04	0.07	-0.06	0.10	0.03	0.08	0.19	-0.22	-0.16	0.14
2010	-0.33	-0.01	-0.15	0.06	0.13	0.16	-0.07	-0.26	0.23		0.02	0.00	0.06	0.02	0.07	0.06	0.19	0.20	-0.11	-0.12	0.16
2011	-0.11	-0.05	-0.08	0.10	0.10	0.01	0.08	-0.01	0.13		0.03	-0.01	0.01	-0.08	0.08	0.02	0.04	0.05	-0.13	-0.12	0.08
2012	-0.23	-0.26	-0.17	0.10	0.01	0.11	0.19	0.13	0.00		0.09	-0.02	0.16	-0.08	0.07	-0.06	0.10	0.16	-0.13	-0.15	0.04
2013	-0.08	-0.10	0.02	0.05	0.04	-0.02	0.13	0.07	0.06		0.11	-0.05	0.14	-0.15	0.08	0.03	-0.12	0.05	-0.05	-0.06	0.14
2014	-0.02	-0.22	-0.09	0.16	0.09	0.01	0.03	0.05	0.11		0.03	0.05	-0.07	-0.05	0.10	0.09	0.11	0.03	-0.19	-0.18	0.05
2015	-0.02	-0.31	-0.06	0.13	0.09	0.12	0.20	0.13	0.20		0.12	-0.41	0.13	-0.20	0.12	0.04	0.15	0.21	-0.26	-0.26	0.11
2016	-0.02	-0.43	-0.11	-0.02	0.13	0.17	0.21	0.19	0.23		0.19	-0.40	0.08	0.01	0.20	-0.03	0.18	0.04	-0.23	-0.26	0.13
2017	-0.37	-0.33	-0.02	0.02	0.15	0.26	0.15	0.06	0.27		0.17	-0.15	-0.04	-0.11	0.27	-0.15	0.23	-0.01	-0.16	-0.14	0.10
2018	-0.31	-0.26	0.00	-0.04	0.13	0.18	0.11	0.05	0.22		0.18	-0.05	-0.04	0.07	0.01	-0.11	0.02	-0.05	-0.04	-0.02	0.06
2019	-0.28	-0.30	-0.04	0.15	0.12	0.24	0.24	0.11	0.20		0.22	-0.11	-0.23	0.02	0.16	-0.11	0.18	-0.03	-0.16	-0.17	0.19
																					1.59

6.5 Conclusion and Policy Implications

This chapter investigated application of market data as a proxy to map the interlinkages of the US financial system. We employed datasets of US statistics covering the period 2002–2019 to capture several crises using PCA and Granger causality. The findings show that the pairwise returns correlation is significant at the 5% level and indicates initial (pre-crisis) interconnectedness and co-movement in the financial market. Following Billio et al. (2012), the first three principal components capture a significant portion of the returns variance. The results indicate an increase of interlinkages in the financial system during crises and highlight the importance of the banking sector in the US financial market.

Applying Granger causality, banking and insurances entities were identified as systemically important institutions. Centrality was proven as a good proxy for identifying the central company(ies) in the system. We also used Diebold and Yılmaz's (2014) pairwise direction variance decomposition with Granger. The results indicate that regulators must validate and calibrate any measure of systemically important institutions' risk exposure and systematic risk, and that such measurements must consider multiple, complementary factors.

Further study of interconnectedness using extensive balance sheet data (as compiled by regulators) to identify SIFIs is appealing, as these should provide a clearer picture of systematic risk. The next chapter undertakes this analysis using Indonesian bank data and employs the market models of CoVaR, MES and SRISK.

A. Robustness Test

1. Linear Regression

To detect the initial correlation among the sample, represented as variable to the benchmark index, we run simple linear regression. The regression results provide the association for each entity variable, as represented by the coefficient to the benchmark. The results also show co-movement, whether positive or negative. Stata calculation shows that the full sample period, all entities except for FMCC, FNMA and COF are statistically significant, with positive correlation at 5% confidence level to the benchmark index SP 500.

Source	SS	df	MS			
				Number of obs	=	1,749
				F(20, 1728)	=	367.48
Model	.151540576	20	.007577029	Prob > F	=	0.0000
Residual	.035628989	1,728	.000020619	R-squared	=	0.8096
				Adj R-squared	=	0.8074
Total	.187169566	1,748	.000107076	Root MSE	=	.00454

SP500	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
AIG	.0315306	.0068374	4.61	0.000	.0181202	.044941
ALL	.0408027	.0120024	3.40	0.001	.0172618	.0643435
BRK	.0225874	.011393	1.98	0.048	.0002418	.0449329
MET	.062454	.0100319	6.23	0.000	.0427781	.0821299
PRU	.037004	.0098464	3.76	0.000	.0176918	.0563162
BAC	-.0545769	.0121075	-4.51	0.000	-.0783237	-.0308301
C	.0585753	.0112353	5.21	0.000	.0365392	.0806114
GS	.089933	.0113774	7.90	0.000	.067618	.112248
JPM	.046336	.0095589	4.85	0.000	.0275876	.0650843
LEH	-.0150163	.0039628	-3.79	0.000	-.0227887	-.0072438
MS	.0441394	.0099451	4.44	0.000	.0246337	.063645
AXP	.1156941	.0101526	11.40	0.000	.0957815	.1356067
BK	.0447305	.0094347	4.74	0.000	.026226	.0632351
COF	.0066071	.005285	1.25	0.211	-.0037585	.0169727
PNC	.0495858	.0109517	4.53	0.000	.0281057	.0710658
STT	.0527199	.0093002	5.67	0.000	.0344791	.0709608
USB	.0485494	.0128045	3.79	0.000	.0234355	.0736634
WFC	-.0429752	.0118619	-3.62	0.000	-.0662404	-.0197099
FMCC	-.010682	.0060303	-1.77	0.077	-.0225095	.0011455
FNMA	.0051782	.0055859	0.93	0.354	-.0057777	.0161341
_cons	-.0000794	.0001095	-0.73	0.469	-.0002941	.0001353

2. Balance Sheet Stylised Fact Network Model

In the network theory model, nodes represent banks, financial institutions, or firms. The nodes interact through edges, which depict node interconnections (Eisenberg & Noe 2001; Gai & Kapadia 2010). The edges could stem from interbank assets or interbank liabilities, for example, securities such as subprime mortgages during the 2008 global financial crises. Each bank manages its liquidity to manage cash and finance their operational needs. We use Gai and Kapadia (2010) to model the interconnectedness based on the stylised fact of bank balance. The correlated exposures of interbank assets and liabilities are more pronounced number to graph the network map of banks interaction. Bank solvency is $(1-\emptyset)\ A_i^{IB} + qA_i^M - L_i^{IB} - D_i > 0$ or the equation in the other form $\emptyset < \frac{K_i-(1-q)A_i^M}{A_i^{IB}}\ for\ A_i^{IB} \neq 0$, where $K_i = A_i^{IB} + A_i^M - L_i^{IB} - D_i$ is the capital buffer. For the crisis to spread to other banks in the system, $\frac{K_i-(1-q)A_i^M}{A_i^{IB}} < \frac{1}{j_i}$. Bank with in-degree j is vulnerable with $v_j = P\left[\frac{K_i-(1-q)A_i^M}{A_i^{IB}} < \frac{1}{j}\right]$, where $j \geq 1$ and the joint degree distribution of a vulnerable bank is $G(x,y) = \sum_{j,k} v_j \,.\, p_{jk} \,.\, x^j \,.\, \mathrm{y}^{\mathrm{k}}$.

The interbank assets of one bank will equal the interbank liabilities of its counterpart. That is, average in-degree (1/n) $\sum_i j_i = \sum_{j,k} jp_{jk}$ equals average out-degree (1/n) $\sum_i k_i = \sum_{j,k} kp_{jk}$. Therefore, $z = \sum_{j,k} j\, p_{jk} = \sum_{j,k} k\ p_{jk}$. From $G(x,y)$ for the link disperse from a random chosen vulnerable bank is:

$$G_0(y) = G(1,y)$$
$$= \sum_{j,k} v_j \,.\, p_{jk} \,.\, \mathrm{y}^{\mathrm{k}}$$
$$G(1,1) = G_0(1)$$
$$= \sum_{j,k} v_j \,.\, p_{jk}$$

For the financial instability that does propagate, they define $v_j . r_{jk}$ as the degree of distribution of a random vulnerable bank. Many in-degree or links to one bank will increase the probability jp_{jk} for it to be a network counterpart of the chosen bank. The number of outgoing placements leaving a randomly chosen bank vulnerable bank is:

$$G_1(y) = \sum_{j,k} \quad v_j . r_{jk} . y^k \ = \frac{\sum_{j,k} \quad v_j \cdot j \cdot p_{jk} \cdot y^k}{\sum_{j,k} \quad j \cdot p_{jk}}$$

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Chapter 7: Macroeconomics of Systemic Risk: Transmission Channels and Technical Integration

Creating a balanced assessment of SIFIs requires integration of macro and micro granular datasets. This chapter investigates how macroeconomic shocks affect systemic risk through several transmission channels. Employing Indonesian bank datasets for the period 2008–2019, we regressed three market models—CoVaR, MES and SRISK—using fixed effects, random effects and pooled OLS, and checked the unobserved variables with the finite mixture model. The findings shows that stock beta, market index and exchange rate volatility amplify systemic risk, while the liquidity spread outcome varies depending on different model variables and the deepness of a country's financial market. We propose a practical systemic risk assessment framework and technical integration to capture overall risk endogenously and externally expose SIFIs.

7.1 Introduction

Prior chapters have shown that market data can be a good proxy for identifying SIBs or SIFIs. In Chapter 4, we identified SIBs using the market models of CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012) and SRISK (Brownlees & Engle 2017) and compared the results with those of the Basel indicator-based methodology (BCBS 2018) employing prudential micro data. In Chapters 5 and 6, we used PCA and Granger centrality (Billio et al. 2012) to estimate the robustness of returns variance, from which we can detect risk commonality and co-movement to scan for interconnectedness in the financial system. Several Granger techniques also allow us to identify SIFIs. The differences between Chapters 5 and 6 were the datasets and methods used. Chapter 5, using granular Indonesian bank data supplied by the regulator, contributed to our knowledge of market data findings' concurrence with Basel. Conversely, the analyses in Chapter 6 were based on publicly available US financial market data. In that chapter, we extended our interconnectedness analysis by using PCA, Granger and pairwise directional variance decomposition (Diebold & Yılmaz 2014). In line with the research objectives, Chapter 7 investigates how macro variables could affect the SIFIs list and by what transmission channels this occurs. The later sections of this chapter also provide technical calculations that could be useful for bank supervisors to integrate macroeconomic variables into their systemic risk assessment.

Current systemic risk methodologies mostly focus on individual SIFI's aspects and how their failure may affect the economy using publicly available data. ECB (2009a) advised the importance of two-sided interaction between the individual financial institution and the economy. De Bandt and Hartmann (2000) showed few researchers have considered macroeconomic indicators that may be behind contagious default. Since 2000, however, there an increasing number of systemic risk academics have use macroeconomic indicators to build the financial stress indexes and model systemic risk. Bisias et al. (2012) listed the macroeconomic indicators used in systemic risk analytics as asset-price boom, property price, macroprudential regulation, GDP stress test, risk topography and several others. Use of macroeconomic indicators to analyse systemic risk has gained popularity following the 2008 global financial crises. However, they are mostly independently estimated as stress test tools or assessed separately from institutional-level data models. Understanding the condition of the economy to address financial contagion will provide regulators and policymakers with a holistic approach. The chapter combines the Basel indicator-based model and macroeconomic variables to assess SIBs from two-sided interaction (micro and macro perspective). The outputs are practically useful for regulatory bodies to identify SIBs and their effects on the financial system.

This chapter raises the questions: 1) How does macroeconomics affect systemic risk and what variables could bring externality to SIBs?, and 2) How can we integrate the macro and micro granular data into the assessment framework and technical calculation of systemic risk? We use three empirical approaches of systemic risk quantification—CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012) and SRISK (Brownlees & Engle 2017)—to answer these questions. We regress the models using linear, ARCH (1,1) and GARCH(1,1), employing Indonesian bank datasets for the period 2008–2019. We also propose a practical, updated assessment framework and technical integration calculation to better capture overall risk.

The findings are as follows:

1. Stock beta, market index volatility and exchange rate volatility amplify the transmission of systemic risk. Further, change in anchor interest rate by a policymaker is proven to be significant, but the effect varies among the market models. The difference could be due to the employed variables and differences in interest rate time horizon. The effect of liquidity spread differs depending on the model used.

2. Practical improvement steps are proposed for the systemic risk assessment framework to better capture potential macroeconomic shocks. We also suggest technical integration calculations and ratios. The integrated macro and micro granular data could portray overall risk endogenously and externally expose SIFIs.

This chapter is structured as follows. Section 7.2 reviews the literature and highlights the possible channels of macroeconomic shocks affecting systemic risk, Section 7.3 details the methodology used, Section 7.4 presents the analytical results and interpretation, and Section 7.5 draws conclusions and makes policy recommendations.

7.2 Literature Review

7.2.1 Macroeconomics and Financial Crises

Studies on SIBs and systemic risk incorporate a mixture of variables, both micro-level or bank balance sheet and macroeconomic data. ECB advised the importance of two-sided interaction between the individual financial institution and the economy:

> between a horizontal perspective of systemic risk, where attention is confined to the financial system, and a vertical perspective of systemic risk in which the two-sided interaction between the financial system and the economy at large is taken into account as well (ECB 2009a).

De Bandt and Hartmann (2000) showed few researchers have considered macroeconomic indicators that may be behind contagious default. Since 2000, however, an increasing number of systemic risk academics have used macroeconomic indicators to build the financial stress indexes and model systemic risk. Bisias et al. (2012) listed the macroeconomic indicators used in systemic risk analytics as asset-price boom, property price, macroprudential regulation, GDP stress test, risk topography and several others. De Mendonça and Silva (2018) used ΔCoVaR to analyse Brazilian banks from 2011–2015 and highlighted the importance of bank liquidity, profitability, leverage and interest rate to assess systemic risk. They noted that leverage increases systemic risk because banks become more vulnerable to shocks. Additionally, higher returns and increase of monetary policy rate also amplify systemic risk. Conversely, more proportion in liquid total assets could lower systemic risk. Tram and Thi Thanh Hoai (2021) elaborated on the connection of macroeconomics and systemic risk using SES and regressing it using OLS, REM, FEM and SGMM. Using 29 Vietnam financial institutions' data for 2010–2018, they found that economic growth and interest rate have a positive correlation to systemic risk and exchange rate has a negative correlation to systemic risk. Ramos-Tallada (2015) elaborated on the characteristics of bank lending channels to monetary shocks such as external finance premium and the money market rate in combination with micro banks' granularity like liquidity ratio, capital ratio, size and foreign ownership. He concluded that lending supply is significantly sensitive to money market rate and external finance premium more sensitive to monetary shocks after crises. Laséen, Pescatori and Turunen (2017) assessed the effect of interest rate on systemic risk and welfare employing the New Keynesian model. They found that monetary tightening policy surprise by raising interest rates does not necessarily reduce systemic risk when the financial sector is fragile. It is known that various blocks of systemic risk variables from macroeconomics should be considered like an exchange rate (Mayordomo, Rodriguez-Moreno & Peña 2014; Yesin 2013), for example, GDP growth (Festić, Kavkler & Repina 2011; Hirtle et al. 2016; Schleer & Semmler 2015).

From a different point of view but closely linked to banking crises, Moshirian and Wu (2009) employed leading macroeconomic variables (GDP growth rates, real interest rate, inflation rates, exchange rate, domestic credit growth rates, the ratio of M2 to reserves, and volatility of GDP growth rates) to construct banking industry volatility. Then, using the econometric logit model, they tested whether banking industry volatility is a good predictor of banking crises. Cont, Moussa and Santos (2013) investigated Brazilian banks, employing the balance sheet and network structure in 2007–2008 and failed banks' contribution to systemic risk. They came up with the Contagion Index as a metric for the systemic importance of institutions. This measures the expected loss to the network triggered by the default of an institution in a macroeconomic stress scenario. Other research applying macroeconomic indicators and their relation to banking distress include Akhter and Daly (2017), using stock market proxies and T-bond for Australian banking; and Ali and Daly (2010), on macroeconomic determinants of credit risk in the US and Australia using default rates, GDP, six-month T-bill, industrial production, debt-to-GDP ratio.

Further, after the turmoil of the 2008 global financial crisis, regulators and policymakers in some countries constructed financial stress indexes to capture the condition of the whole economy using selected macroeconomic indicators. Previous results in this area will be useful for our study, as they identify variables that could be used for SIB assessment. Illing and Liu (2006) developed a daily financial stress index for the Canadian financial system, grouping 11 macroeconomic indicators (covering banking, foreign exchange, debt and the equity market) and analysing them using GARCH estimation to extract volatility measures. Hollo, Kremer and Lo Duca (2012) proposed a CISS to measure financial system stress. They used 15 indicators classified into four economy segments: money market, equity market, bond market and foreign exchange market for the Eurozone. To construct the index, they applied basic portfolio model theory and considered the time-varying cross-correlation between the sub-indices, where CISS put relatively more weight on situations when stress prevailed. Oet, Dooley and Ong (2015) built a financial stress index for Cleveland, US, to identify systemic risk condition. They proposed six market partitions: credit, funding, real estate, securitisation, foreign exchange and equity markets. They selected between several index weighting methodologies across a variety of monitoring frequencies through comparison against a volatility-based benchmark series. MacDonald, Sogiakas and Tsopanakis (2018) applied multivariate GARCH and calculated banking sector variables, money market, equity market and bond market. Assessing the Eurozone economies, they were able to capture the market dependencies and volatilities where the banking and money markets show important stress transmission.

OJK has established a Coincidence Index to assess pressures on the financial market on an ongoing basis. This was developed based on Hollo, Kremer and Lo Duca (2012) and has undergone several modifications, with the latest iteration being the 3.0 version. The index divides the pressure into five segments:

- Money market—bid ask spreads of five-year CDS and 10-year bond yield.
- Capital market—market index (IHSG) and market returns volatility (1 month)
- Interbank money market—JIBOR overnight.
- Exchange rate—exchange rate (IDR/USD) and implied volatility.
- Financial block—probability of default.

Additionally, OJK has set an early warning system surveillance platform to estimate cyclical financial sector distress in future. The newest version calculates several leading indicators: banking (non-core liabilities and banking total loan), monetary (central bank reserve and five-year CDS), real economy (commodity price, consumer, business and benchmark index).

As shown above, although few academics used macroeconomic variables in systemic risk analysis prior to 2000 (De Bandt & Hartmann 2000), an increasing number of systemic risk academics have since used macroeconomic indicators to predict financial distress. For our study, previous financial stress studies' results provide valuable insights for our selection of macroeconomic indicators to complement banks' data in integrated SIB analysis.

7.2.2 Basel Committee on Banking Supervision Guideline

The first guideline to determine SIBs was issued by BCBS in 2011 (BCBS 2011). These standards were updated in 2013 and 2018 (BCBS 2013, 2018). The rationale for adopting additional policy measures for G-SIBs is based on the 'negative externalities' created by SIBs, which current regulatory policies do not adequately address (BCBS 2012). Although BCBS admitted that the indicators do not precisely measure the specific attributes of SIBs, the proxies are designed to identify the central aspect of SIB status. Despite its simplicity, BCBS claims the method is more robust than currently available model-based measurement approaches and methodologies that rely on a small set of indicators or market variables (BCBS 2018). The indicators and categories of the most recent guideline are shown in Table 7.1.

Table 7.1. Indicator-based Measurement Approach

Category (weighting)	Individual indicator	Indicator weighting
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio*	20%
Interconnectedness (20%)	Intra-financial system assets*	6.67%
	Intra-financial system liabilities*	6.67%
	Securities outstanding*	6.67%
Substitutability/financial institution Infrastructure (20%)	Assets under custody	6.67%
	Payment activity	6.67%
	Underwritten transactions in debt and equity markets	3.33%
	Trading volume	3.33%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale securities	6.67%

* Extended scope of consolidation to include insurance activities.
Source: BCBS (2018).

The BCBS G-SIBs guideline categorises bank activities into five main groups consisting of 13 indicators. The latest update introduced trading volume indicator, modified the weightings in the substitutability category, and extended the scope of consolidation to insurance subsidiaries (BCBS 2018). To make reports comparable between BCBS member countries, banks' data are converted to euros using the exchange rate published on the BCBS website. To calculate the score for a given indicator, a bank's reported value for the indicator is divided by the corresponding total sample (BCBS 2014). For the purpose of creating the list of G-SIBs, the guideline takes the most significant 75 banks as determined by the Basel III leverage ratio exposure measure. BCBS allows some departure from the BCBS (2012) guideline for domestic regulators to better capture specific D-SIBs characteristics and country externalities.

Our study explores how macroeconomic shocks affect systemic risk through several transmission channels. Employing Indonesian bank datasets for 2008–2019, we regressed three market models—CoVaR, MES and SRISK—using linear, ARCH and GARCH. The findings shows that stock beta, market index and exchange rate volatility amplify systemic risk, while the liquidity spread outcome varies depending on different model variables and the deepness of a country's financial market. We propose a practical systemic risk assessment framework and technical integration to capture overall risk endogenously and externally expose SIFIs. The results will be beneficial for policymakers to monitor and mitigate systemic risk using a more holistic approach.

7.3 Data and Methodology

7.3.1 Source of Data

The datasets represent all commercial banks listed on the JSX in the period 2008–2019. The sample entities are classified based on their amount of core capital, following OJK (2021). The MS Excel sheet provides the market data (daily frequency) of share price, transaction volume, outstanding shares, stock index and market capitalisation. We also collect granular data from bank balance sheets (quarterly frequency): total assets and total equity. In line with the research objectives, we also gather representative macroeconomics statistics such as exchange rate, T-bill delta, 7D repo rate, credit spread, liquidity spread, TED spread, yield spread, JSX LQ45 excess return, JSX financial sector excess return and JSX VIX.

Market data was sourced from Eikon Thomson Reuters, Bank Indonesia and the author's calculations. The MATLAB coding provided by Belluzo (2020) on the GitHub website was used for analyses. The datasets are for 27 actively trading banks listed on the JSX during the period 2008–2019. The sample banks are listed in Table 7.2.

Table 7.2. Indonesian Dataset Sample

No.	Ticker	Bank	KBMI group
1	BBCA	PT. Bank Central Asia Tbk.	4
2	BBRI	PT. Bank Rakyat Indonesia (Persero) Tbk.	4
3	BMRI	PT. Bank Mandiri (Persero) Tbk.	4
4	BBNI	PT. Bank Negara Indonesia (Persero) Tbk.	4
5	MEGA	PT. Bank Mega Tbk.	3
6	MAYA	PT. Bank Mayapada Internasional Tbk.	3
7	BNLI	PT. Bank Permata Tbk.	3
8	BDMN	PT. Bank Danamon Indonesia Tbk.	3
9	PNBN	PT. Bank Pan Indonesia Tbk.	3
10	NISP	PT. Bank OCBC NISP Tbk.	3
11	BNGA	PT. Bank CIMB Niaga Tbk.	3

No.	Ticker	Bank	KBMI group
12	BTPN	PT. Bank BTPN Tbk.	3
13	BNII	PT. Bank Maybank Indonesia Tbk.	3
14	BJBR	PT. Bank Pembangunan Daerah Jawa Barat Tbk.	2
15	BBTN	PT. Bank Tabungan Negara (Persero) Tbk.	3
16	BSIM	PT. Bank Sinarmas Tbk.	1
17	BJTM	PT. Bank Pembangunan Daerah Jawa Timur Tbk.	2
18	SDRA	PT. Bank Woori Saudara Indonesia Tbk.	2
19	BACA	PT. Bank Capital Indonesia Tbk.	1
20	AGRO	PT. BRI Agroniaga Tbk.	1
21	CCBI	PT. Bank China Construction Indonesia Tbk.	1
22	BBKP	PT. Bank Bukopin Tbk.	2
23	BABP	PT. Bank MNC Internasional Tbk.	1
24	BKSW	PT. Bank QNB Indonesia Tbk.	1
25	INPC	PT. Bank Artha Graha Internasional Tbk.	1
26	BNBA	PT. Bank Bumi Arta Tbk.	1
27	BVIC	PT. Bank Victoria Internasional Tbk.	1

7.3.2 Model Estimation

7.3.2.1 CoVaR

Adrian and Brunnermeier (2016) introduced CoVaR in 2008 and have provided several updates. The root is Jorion's (2007) VaR study, which represented the most that a bank loses, with confidence level 1 – α, the parameter of α being 1% or 5%, $Pr(R< -VaR_{\alpha}) = \alpha$.

CoVaR corresponds to the VaR of the market returns condition of certain events, $C(R_t^i)$, of firms *i*:

$$\Pr\left(R_{mt} \leq CoVaR_t^{m \mid rit} \mid C_{rit}\right) = \alpha$$

$$X^t i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i$$

$$X_t^{sysli} = \alpha_q^{sys|i} + \gamma_q^{sysIi} M_{t-1} + \beta_q^{sys|i} x_t^i + \varepsilon_{q,t}^{sys|i}$$

These predict the value of the regression to obtain:

$$VaR_{q,t}^i = \alpha_q^i + \gamma_q^i M_{t-1}$$

$$CoVaR_{q,t}^{sysli} = \alpha'^{sys|i}_q + \gamma'^{sysIi}_q M_{t-1} + \beta_q'^{sys|i} x_t^i . VaR_{q,t}^i$$

CoVaR is the difference of financial system VaR condition of firm *i* in financial distress and financial system VaR when firm *i* is in a median state. CoVaR represents the systemic risk contribution of firm *i* to the financial system:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^i + CoVaR_{50,t}^i$$

7.3.2.2 MES

MES was proposed by Acharya, Engle and Richardson (2012), who used two standards to measure firm-level risk: value at risk (VaR) and expected shortfall (ES). VaR is the most that a bank loses, with confidence level $1 - \alpha$, the parameter of α being 1% or 5%:

$$Pr(R < -VaR_{\alpha}) = \alpha$$

ES is the expected loss conditional on the loss being greater than the VaR or the average of returns on days when the portfolio's loss exceeds its VaR limit:

$$ES_{\alpha} = - E\, [R/R \leq - VaR_{\alpha}]$$

Acharya et al. (2017) focus on ES rather than VaR, as the latter is not robust in the sense that negative payoff below the thresholds 1% or 5% are not captured and the sum of two portfolios' VaR could be higher than the sum of an individual VaR.

To calculate the contribution of bank-wide losses into groups or trading desk contribution, the next step is decomposing bank return R into the sum of each group's return r_i:

$$R = \sum_i = y_i\, r_i$$

where y_{i} is the weight of group i in the total portfolio. Then:

$$ES = - \sum_i y_i\, E(\, r_i \mid R \leq - VaR\,)$$

The sensitivity of overall risk to exposure y_i to each group i is:

$$\frac{\delta ES\alpha}{\delta yi} = E(\, r_i \mid R \leq - VaR\,) \equiv MES_{\alpha}^{i}$$

where MES^{i} is group i's losses or MES when the firm is doing poorly.

7.3.2.3 SRISK

Following from Acharya, Engle and Richardson (2012), Brownlees and Engle (2017) theorised that the risk contribution of a financial firm to systemic risk is a function of the firm's size, leverage and risk. Using balance sheet and market data, they calculated the expected capital shortfall over longer period of market decline called LRMES. SRISK considers the equity volatility, return distribution, correlation, size and leverage level of firms. SIFIs are ranked according to the highest SRISK, and the total will be the undercapitalisation of the whole financial system:

$$SRISK_{i,t} = E_{t-1}\,(\text{Capital shortfall}_i \mid \text{Crisis})$$

Estimation of capital shortfall uses bivariate daily equity returns of firms and market index, where volatilities follow asymmetric GARCH and DCC processes. To simulate a crisis, the market index is assumed to fall by 40% over six months, and projection, volatilities and correlation change over time to calculate the tail dependence:

$$CS_{i,t} = kA_{i,t} - W_{i,t}$$

$$CS_{i,t} = k(D_{i,t} + W_{i,t}) - W_{i,t}$$

where:

$W_{i,t}$ = market value of equity

$D_{i,t}$ = book value of debt

$A_{i,t}$ = book value of assets

k = prudential capital fraction which is set to 8%

Based on the above formula, when capital shortfall is negative, firms that have positive or surplus working capital can operate normally, but the opposite holds true when capital shortfall is positive and firms are under distress. Firm capital shortfall causes negative externalities only if it occurs when the whole system is already under distress, the multiperiod market return of period t+1 and t+h as $R_{mt+1:t+h}$ and the systemic event reported when $R_{mt+1:t+h} < C$, where C is the market decline threshold:

$$SRISK_{i,t} = E_t\,(CS_{it+h} \mid R_{mt+1:t+h} < C$$
$$= k\,E_t\,(D_{i,t+h} \mid R_{mt+1:t+h} < C) - (1-k)E_t(W_{it+h} \mid R_{mt+1:t+h} < C)$$

A assumption is made by Brownlees and Engle (2017) when debtors are unable to renegotiate their debts during crises:

$$SRISK_{i,t} = kD_{it} - (1-k)\,W_{it}\,(1 - \mathrm{LRMES})$$
$$= W_{i,t}\,[\mathrm{kLVG}_{it} + (1\text{-}k)\,\mathrm{LRMES}_{it} - 1]$$

where:

LVG = leverage ratio $(D_{it} + W_{it}) / W_{it}$

LRMES = average of firm equity returns approximated as 1 – exp (–18 x MES) to represent the expected loss over a six-month period with 40% market fall condition.

The contribution or systemic share of firm *i* SRISK is calculated as:

$$\mathrm{SRISK\%}_{i,t} = \frac{\mathrm{SRISKi,t}}{\Sigma j \in J\ \mathrm{SRISKj,t}}$$

where J = firms with positive SRISK.

7.4 Results

7.4.1 Statistics Summary

Our discussion comprises three major analysis blocks. First, to generate the systemic risk contribution of each bank over the sample period using CoVaR, MES and SRISK (Section 7.4.2). Second, to regress the estimation results derived from step 1 to macroeconomic variables (e.g., beta, exchange rate, Fed fund rate, T-bill delta, JKSE volatility index, liquidity spread and TED spread) (Section 7.4.3). Third, to propose possible technical integrations for the BCBS (2018) indicator-based approach to capture macroeconomic effects on systemic risk (Section 7.4.4).

The preliminary data process involved sorting and adjusting data composition, with the statistics summary displayed in Table 7.3. Pairwise correlation between variables is presented in Table 7.4.

Table 7.3. Descriptive Statistics

	N	Mean	Min	Max	SD	Variance	Kurtosis
Beta	50328	.631	-3.821	6.539	.572	.327	6.614
DCOVAR	50328	0	0.000	0	0	0	5.983
MES	50328	.014	0.000	.117	.01	0	5.954
SRISK	50328	732161.19	0.000	3.607e+07	2.411e+06	5.815e+12	47.347
EXC RATE	50328	12789.244	9450.000	15253	1527.553	2333417.4	2.796
FFR	50328	6.078	4.250	7.75	1.159	1.343	1.633
TBILL DELTA	50328	-.004	-65.220	67.33	13.029	169.746	6.188
JKSE VIX	50328	10.407	0.010	92.02	10.346	107.047	10.39
LIQ SPR	50328	1.244	-0.110	3.13	.591	.349	2.91
TED SPR	50328	4.443	1.900	6.54	1.186	1.406	1.783

Table 7.4. Pairwise Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Beta	1.000													
(2) COVAR	-0.045*	1.000												
	(0.000)													
(3) DCOVAR	0.678*	0.030*	1.000											
	(0.000)	(0.000)												
(4) MES	0.848*	0.071*	0.644*	1.000										
	(0.000)	(0.000)	(0.000)											
(5) SRISK	0.478*	-0.012*	0.335*	0.358*	1.000									
	(0.000)	(0.005)	(0.000)	(0.000)										
(6) DCOVAR_1	0.040*	0.007	0.022*	0.076*	0.005	1.000								
	(0.000)	(0.108)	(0.000)	(0.000)	(0.292)									
(7) MES_1	-0.003	0.003	-0.014*	0.001	-0.006	0.181*	1.000							
	(0.559)	(0.465)	(0.001)	(0.811)	(0.160)	(0.000)								
(8) SRISK_1	0.005	-0.004	0.000	0.004	0.003	0.008	0.002	1.000						
	(0.295)	(0.343)	(0.967)	(0.406)	(0.537)	(0.057)	(0.696)							
(9) EXC_RATE	0.050*	-0.060*	-0.006	0.041*	0.146*	0.005	0.004	0.006	1.000					
	(0.000)	(0.000)	(0.149)	(0.000)	(0.000)	(0.262)	(0.361)	(0.181)						
(10) FFR	-0.025*	0.113*	0.017*	0.082*	-0.015*	-0.004	-0.001	-0.007	-0.205*	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.375)	(0.844)	(0.123)	(0.000)					
(11) TBILL_DELTA	0.001	-0.015*	0.001	0.006	0.000	0.009*	0.002	0.004	0.000	-0.002	1.000			
	(0.899)	(0.001)	(0.739)	(0.201)	(0.943)	(0.040)	(0.649)	(0.328)	(0.970)	(0.664)				
(12) JKSE_VIX	-0.058*	0.162*	0.039*	0.100*	-0.021*	-0.007	-0.002	-0.004	-0.057*	0.119*	-0.630*	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.127)	(0.632)	(0.320)	(0.000)	(0.000)	(0.000)			
(13) LIQ_SPR	0.031*	-0.005	0.009*	0.060*	0.030*	-0.002	0.000	0.000	0.249*	0.340*	-0.011*	0.014*	1.000	
	(0.000)	(0.311)	(0.042)	(0.000)	(0.000)	(0.600)	(0.951)	(0.952)	(0.000)	(0.000)	(0.012)	(0.002)		
(14) TED_SPR	-0.013*	0.107*	0.019*	0.094*	-0.040*	-0.002	-0.003	-0.008	-0.252*	0.818*	0.004	0.105*	0.208*	1.000
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.732)	(0.457)	(0.089)	(0.000)	(0.000)	(0.388)	(0.000)	(0.000)	

*** p<0.01, ** p<0.05, * p<0.1.

7.4.2 Systemic Risk Based on Market Models

7.4.2.1 CoVaR

As shown in Table 7.5, CoVaR SIB rankings over the sample period are dominated by the biggest (KBMI 4) commercial Indonesian banks (total equity of more than Rp 70 trillion each). These are the major players in the Indonesian banking market and contribute the most to systematic risk.

Table 7.5. CoVaR

Bank	2008		2009		2010		2011		2012		2013	
	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank
BCA	30.0%	2	25.4%	1	26.6%	1	21.7%	2	30.9%	1	25.1%	1
BRI	15.8%	3	9.0%	4	9.7%	4	10.1%	5	6.4%	6	10.7%	3
BMRI	30.9%	1	17.0%	2	19.7%	2	22.4%	1	16.9%	2	22.5%	2
BNI	6.1%	4	9.2%	3	8.5%	5	10.2%	4	8.1%	4	8.7%	4
MEGA	1.1%		8.0%	5	1.8%		2.0%		2.1%		1.7%	
BDMN	1.5%		1.6%		2.0%		1.7%		1.4%		2.1%	
PNBN	0.9%		1.2%		1.0%		1.5%		1.1%		1.1%	
BJBR	3.5%		5.7%	6	10.5%	3	10.3%	3	11.4%	3	7.3%	5
BTN	0.0%		1.2%		3.0%		2.2%		2.3%		3.1%	
BSIM	0.4%		0.6%		5.0%	6	3.2%		1.2%		0.8%	
BJTM	0.1%		0.1%		0.1%		0.2%		7.1%	5	6.2%	6
SDRA	1.4%		2.9%		2.1%		2.9%		2.4%		2.3%	
BACA	2.1%		3.6%		3.5%		4.1%		2.6%		2.5%	
AGRO	0.2%		1.1%		0.5%		0.5%		0.5%		0.6%	
CCBI	1.5%		4.4%		0.7%		0.4%		0.3%		0.7%	
BBKP	1.7%		2.2%		2.1%		3.2%		2.0%		2.2%	
MNC	1.2%		4.3%		1.7%		2.1%		1.8%		1.0%	
Others—10 banks	1.5%		2.5%		1.3%		1.3%		1.3%		1.5%	

Bank	2014		2015		2016		2017		2018		2019	
	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank
BCA	19.0%	2	24.7%	1	14.9%	3	20.1%	1	20.6%	1	19.7%	1
BRI	9.9%	4	11.3%	3	7.0%	5	9.3%	5	7.9%	5	7.5%	5
BMRI	19.4%	1	20.9%	2	14.0%	4	16.9%	2	18.9%	2	15.2%	3
BNI	11.4%	3	8.6%	5	6.7%	6	10.5%	3	10.2%	4	9.6%	4
MEGA	2.2%		1.6%		1.3%		3.2%		2.4%		1.9%	
BDMN	2.0%		1.9%		1.3%		3.7%		1.8%		1.8%	
PNBN	1.4%		1.1%		0.9%		1.3%		1.6%		1.4%	
BJBR	9.7%	5	8.9%	4	23.5%	1	9.4%	4	11.9%	3	16.9%	2
BTN	2.9%		1.4%		2.6%		2.2%		3.2%		2.5%	
BSIM	1.5%		1.4%		0.8%		5.0%		2.5%		2.6%	
BJTM	7.9%	6	6.3%	6	17.2%	2	6.5%	6	7.0%	6	6.0%	6
SDRA	2.8%		2.2%		1.7%		2.6%		3.3%		5.7%	7
BACA	3.4%		3.2%		1.9%		2.8%		3.4%		2.5%	
BBKP	2.3%		1.8%		2.3%		2.6%		2.5%		2.7%	
MNC	1.3%		1.2%		1.1%		1.0%		0.8%		0.8%	
Others—12 banks	2.9%		3.5%		2.6%		2.8%		2.2%		3.1%	

7.4.2.2 MES

As shown in Table 7.6, MES shortlisted more banks and noticeably more unstable bank rankings than CoVaR. Such ranking volatility is one of the MES model's disadvantages compared to other market models. It would be difficult for a bank supervisor to impose the systemic capital change, since capital shortage injection by shareholders usually takes time to be approved. Again, KBMI 4 commercial banks are the main contributors to systemic risk.

Table 7.6. Marginal Expected Shortfall

Bank	2008		2009		2010		2011		2012		2013	
	% to sys	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**
BCA	10.77%	3	8.00%	4	7.12%	5	5.29%	8	9.79%	1	6.77%	6
BRI	16.51%	1	6.99%	6	8.00%	2	6.52%	6	5.62%	7	8.45%	2
BMRI	15.55%	2	7.50%	5	8.33%	1	7.06%	5	7.76%	3	7.75%	3
BNI	9.88%	4	13.02%	1	6.89%	6	10.18%	1	1.20%		10.51%	1
BDMN	6.67%	6	6.77%	7	7.75%	3	4.56%		6.50%	5	6.93%	4
PNBN	8.37%	5	6.60%	9	6.74%	7	8.01%	2	9.74%	2	6.91%	5
BTPN	1.20%		5.10%	11	3.31%		5.77%	7	4.05%		4.23%	
Maybank	1.38%		5.01%	12	3.61%		4.16%		3.34%		2.56%	
BJBR	0.64%		0.95%		6.42%	8	4.99%		5.80%	6	3.14%	
BTN	0.09%		2.92%		7.63%	4	4.65%		4.28%		5.77%	7
BSIM	0.19%		0.28%		−0.45%		7.63%	3	2.57%		0.71%	
SDRA	4.41%		5.81%	10	4.56%		5.28%	9	3.80%		3.89%	
AGRO	2.83%		6.79%	7	3.41%		2.41%		3.92%		2.18%	
BBKP	5.66%	7	6.77%	8	5.32%	9	7.17%	4	7.00%	4	5.22%	8
MNC	2.44%		9.24%	2	1.19%		0.07%		3.45%		3.78%	
BAG	0.98%		4.98%		3.59%		5.16%	10	1.78%		2.08%	
BNBA	3.94%		3.47%		2.11%		2.27%		2.25%		1.65%	
BVIC	3.47%		8.75%	3	3.38%		3.88%		4.45%		4.00%	
Others—9 banks	8.92%		−5.51%		13.17%		7.22%		13.43%		12.30%	
Bank	**2014**		**2015**		**2016**		**2017**		**2018**		**2019**	
	% to sys	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**	**% to sys**	**Rank**
BCA	5.27%	7	7.49%	4	4.07%		6.27%	4	4.45%		5.21%	9
BRI	7.90%	2	9.89%	2	6.01%	6	8.14%	3	6.36%	6	5.77%	7
BMRI	7.02%	3	8.72%	3	5.58%	8	5.83%	6	7.33%	3	5.50%	8
BNI	12.10%	1	10.80%	1	8.33%	1	12.23%	2	11.22%	1	10.36%	2
MEGA	1.93%		1.39%		0.48%		6.16%	5	3.07%		2.04%	
BDMN	6.75%	4	6.69%	5	6.03%	5	17.08%	1	6.83%	5	6.05%	5
PNBN	6.54%	5	5.14%	8	4.94%		1.81%		5.99%	7	6.88%	4
BTPN	3.84%		2.63%		1.97%		3.96%		3.70%		3.91%	
BJBR	4.68%		4.75%		5.10%	9	−0.61%		2.61%		−0.28%	
BTN	6.43%	6	3.10%		7.27%	3	3.04%		8.08%	2	5.21%	10
BJTM	2.57%		3.19%		7.01%	4	0.73%		1.91%		1.79%	
SDRA	4.12%		2.65%		2.03%		2.79%		1.97%		3.92%	
BACA	1.62%		5.18%	7	4.12%		2.38%		2.55%		2.17%	
BNGA	2.55%		1.67%		3.20%		2.26%		3.69%		3.95%	
AGRO	3.25%		3.16%		7.94%	2	3.85%		3.46%		8.88%	3
BBKP	4.96%		4.13%		5.78%	7	5.06%	7	5.95%	8	5.82%	6
MNC	3.73%		5.65%	6	4.15%		2.55%		1.31%		1.35%	
BVIC	2.10%		4.04%		2.92%		3.89%		6.96%	4	12.75%	1
Others—9 banks	12.64%		9.71%		13.06%		12.60%		12.56%		8.70%	

7.4.2.3 SRISK

SRISK measures systemic risk, integrating and complementing other systemic estimation models by using bank size and degree of leverage (Brownlees & Engle 2017). Total aggregate SRISK resembles the total amount of capital shareholders or government need to raise during a financial crisis. SRISK = 0 means that a bank does not have enough capital during a crisis, where there is 40% market decline, and the prudential capital regulation is assumed to be 8%. SRISK estimation results are presented in Table 7.7.

Table 7.7. SRISK

Bank	2008		2009		2010		2011		2012		2013	
	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank
BMRI	31.14%	1	0.00%		0.00%		0.00%		0.00%		0.00%	
BNI	29.17%	2	16.13%	3	0.00%		7.43%	3	0.00%		39.87%	1
BNLI	11.30%	4	24.24%	2	31.85%	2	27.93%	2	0.00%		0.00%	
PNBN	0.00%		0.00%		0.00%		2.47%		70.17%	1	22.02%	3
BNGA	24.61%	3	44.70%	1	67.64%	1	49.54%	1	0.00%		0.00%	
BJBR	0.00%		13.67%	4	0.00%		0.00%		3.83%		0.00%	
BTN	0.00%		0.00%		0.00%		0.00%		0.00%		26.72%	2
BJTM	0.00%		0.00%		0.00%		5.75%	4	0.00%		0.00%	
BBKP	2.81%		0.00%		0.00%		4.04%		18.48%	2	4.55%	
BAG	0.88%		1.26%		0.51%		2.45%		1.95%		2.56%	
BVIC	0.00%		0.00%		0.00%		0.39%		5.57%	3	4.29%	
Others—16 banks	0.00%		0.00%		0.00%		0.00%		0.00%		0.00%	
Bank	**2014**		**2015**		**2016**		**2017**		**2018**		**2019**	
	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank	% to sys	Rank
BNI	0.00%		23.91%	2	26.65%	2	26.11%	2	40.78%	1	49.14%	1
BNGA	19.62%	2	26.94%	1	12.77%	4	0.00%		11.45%	4	10.52%	4
BTPN	0.00%		0.00%		0.00%		0.00%		0.00%		1.97%	
Maybank	0.00%		7.52%	5	0.00%		0.00%		0.26%		1.44%	
BJBR	16.16%	3	10.77%	4	0.00%		0.00%		0.00%		0.00%	
BTN	43.27%	1	13.48%	3	28.09%	1	0.00%		28.55%	2	20.15%	2
BBKP	1.84%		6.62%	6	13.36%	3	52.75%	1	13.36%	3	10.94%	3
BAG	9.18%	4	5.30%	7	3.81%		14.51%	3	2.38%		1.79%	
BNBA	0.93%		0.32%		0.46%		0.00%		0.00%		0.00%	
BVIC	8.19%	5	5.13%	8	4.37%		6.63%	4	3.22%		3.35%	
BACA	0.81%		0.00%		0.58%		0.00%		0.00%		0.00%	
AGRO	0.00%		0.00%		0.00%		0.00%		0.00%		0.70%	
PNBN	0.00%		0.00%		9.90%		0.00%		0.00%		0.00%	
Others—14 banks	0.00%		0.00%		0.00%		0.00%		0.00%		0.00%	

We calculate the stock beta for each entity to capture the macroeconomic market effects on individual banks, with the results presented in Table 7.8. Stock beta represents the likelihood of stock volatility to the benchmark index. As shown in Table 7.8, BKMI 4 banks have a higher beta in all sample windows. On average, the beta was above 1, meaning that BKMI 4 banks are more volatile compared to the JKSE index. BKMI 1–3 banks' beta indicates that these banks will suffer 0.3–0.5 less volatility than the overall market. We note that volatility decreases as banks' offered products and activities decrease; that is, BKMI 4 banks have the highest volatility and BKMI 1 banks (providing basic services and activities) have the lowest volatility. The volatile capital market in Indonesia during 2014 was a result of uncertainties regarding US Federal Reserve quantitative easing and tapering off. For more detailed explanation and discussion of the market model results, please refer to Salim and Daly (2021) and Chapter 4 of this thesis.

Table 7.8. Beta of Sample Groups (2012–2019)

		Mean	Max	Min	St.Dev	Kurtosis	Skewness
2012	BKMI 4	1.175	1.571	0.803	0.177	-0.724	-0.162
	BKMI 3	0.578	0.664	0.484	0.043	-0.698	0.161
	BKMI 2	0.588	0.880	0.440	0.087	0.728	0.928
	BKMI 1	0.325	0.617	0.202	0.063	3.372	0.945
2013	BKMI 4	1.214	1.765	0.718	0.228	-0.664	0.347
	BKMI 3	0.510	0.841	0.317	0.113	0.231	0.756
	BKMI 2	0.507	0.907	0.216	0.149	0.162	0.268
	BKMI 1	0.248	0.456	0.145	0.060	0.861	1.101
2014	BKMI 4	1.715	2.356	1.419	0.163	0.723	0.528
	BKMI 3	0.560	0.763	0.395	0.080	-0.678	-0.101
	BKMI 2	0.538	0.794	0.410	0.061	0.854	0.493
	BKMI 1	0.332	0.584	0.181	0.064	0.477	0.323
2015	BKMI 4	1.463	1.855	1.061	0.160	-0.342	-0.358
	BKMI 3	0.495	0.753	0.277	0.081	-0.013	0.204
	BKMI 2	0.447	0.761	0.267	0.089	0.328	0.496
	BKMI 1	0.343	0.629	0.173	0.086	0.214	0.628
2016	BKMI 4	1.446	1.893	0.987	0.206	-0.742	0.059
	BKMI 3	0.602	1.137	0.388	0.125	1.399	0.831
	BKMI 2	0.569	1.360	0.315	0.156	4.291	1.696
	BKMI 1	0.452	1.248	0.200	0.165	5.292	1.917
2017	BKMI 4	1.506	1.845	1.116	0.154	-0.377	-0.324
	BKMI 3	0.658	1.260	0.018	0.165	3.426	-0.653
	BKMI 2	0.560	1.116	0.022	0.177	2.134	-0.533
	BKMI 1	0.550	0.994	0.240	0.139	0.604	0.766
2018	BKMI 4	1.390	1.825	0.631	0.240	1.738	-1.151
	BKMI 3	0.511	0.810	0.117	0.103	3.205	-1.402
	BKMI 2	0.322	0.604	0.098	0.099	-0.230	0.361
	BKMI 1	0.363	0.509	0.200	0.065	-0.674	-0.210
2019	BKMI 4	1.596	1.959	1.170	0.145	-0.210	-0.542
	BKMI 3	0.704	1.048	0.462	0.115	-0.009	0.515
	BKMI 2	0.609	1.430	0.375	0.126	7.732	1.466
	BKMI 1	0.418	0.637	0.300	0.071	-0.217	0.651

7.4.3 Regression Results

To test macroeconomic variables effects on systemic risk, we employ the equation used by de Mendonça and Silva (2018) and adjusted it to reflect our specific variables:

$$\Delta CoVaR = \beta \Delta CoVaR_{t-1} + \beta BETA + \beta EXC\_R + \beta FFR + \beta TBILL + \beta JKSEVIX + \beta LIQSPR + \beta TEDSPR + \varepsilon$$

$$MES = \beta MES_{t-1} + \beta BETA + \beta EXC\_R + \beta FFR + \beta \Delta TBILL + \beta JKSEVIX + \beta LIQSPR + \beta TEDSPR + \varepsilon$$

$$SRISK = \beta SRISK_{t-1} + \beta BETA + \beta EXC\_R + \beta FFR + \beta \Delta TBILL + \beta JKSEVIX + \beta LIQSPR + \beta TEDSPR + \varepsilon$$

Note that $\Delta CoVaR_{t-1}$, MES_{t-1} and $SRISK_{t-1}$ = ΔCoVaR, MES and SRISK of bank *t* at *t*–1.

BETA	= bank stock beta
EXC_R	= exchange rate
FFR	= central bank funding rate
TBILL	= three-month T-bill rate
JKSEVIX	= JSX volatility index
LIQSPR	= liquidity spread (the difference of three-month repo and three-month T-bill rate)
TEDSPR	= TED spread (the difference of three-month USD LIBOR and three-month T-bill rate)

Based on balanced panel data for daily observations of over 50,000 variables, analyses were undertaken using fixed effects, random effects generalised least square (GLS) and random effects maximum likelihood estimator models. The summary of estimation values is presented in Table 7.9. To check best fit model, we run the Hausman test, where the outcome of H_0 is statistically significant at 0.002 for ΔCoVaR, reflecting that the random effect is consistent. Conversely, using the same test, we fail to reject H_0 for MES at 0.993 and SRISK at 1, inferring that we should choose the fixed effects model over the random effects (see Table 7.10). The SRISK results are suspicious due to the high correlation of ε with the regressor. However, refer to Section 7.4.2.3 and note that the sampled Indonesian banks have sufficient capital even during crises, as reflected in SRISK = 0, which read as autocorrelation in the calculation. ΔCoVaR employing Breusch Pagan Lagrangian test results (see Table 7.11) for random effect reject H_0, prompting us to run the pooled OLS.

Table 7.9. Panel Data Results Summary

	PANEL A. DCOVAR			PANEL B. MES			PANEL C. SRISK		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FE	RE GLS	RE MLS	FE	RE GLS	RE MLS	FE	RE GLS	RE MLS
	FE_DCoVaR	RE.GLS_ DCoVaR	RE.MLS_D CoVaR	FE_MES	RE.GLS_D CoVaR	RE.MLS_ DCoVaR	FE_MES	RE.GLS_D CoVaR	RE.MLS_DCoVa R
DCOVAR_1	0***	0***	0						
	(23.99)	(23.96)	(-.7)						
MES_1	-	-	-	0***	0***	0***			
				(5.56)	(5.56)	(5.56)			
SRISK_1	-	-	-	-	-	-	-0.01	-0.01	-0.01
							(-.71)	(-.71)	(-.71)
Beta	0***	0***	0	.02***	.02***	.02***	20.50***	20.49***	20,49***
	(55.49)	(55.62)	(.)	(253.85)	(254.34)	(254.35)	(88.44)	(88.52)	(88.53)
EXC_RATE	0***	0***	0***	0***	0***	0***	0***	0***	0***
	(-5.05)	(-5.05)	(-13.46)	(16.74)	(16.74)	(16.74)	(38.97)	(38.97)	(38.98)
FFR	0	0	0***	0***	0***	0***	1.91***	1.91***	1.91***
	(.47)	(.48)	(8.86)	(9.7)	(9.7)	(9.7)	(16.12)	(16.12)	(16.12)
TBILL_DELTA	0***	0***	0***	0***	0***	0***	0.02***	0.02***	0.02***
	(30.6)	(30.59)	(33.44)	(63.62)	(63.62)	(63.63)	(3.28)	(3.28)	(3.28)
JKSE_VIX	0***	0***	0***	0***	0***	0***	0.05***	0.05***	0.05***
	(46.88)	(46.87)	(52.02)	(96.6)	(96.6)	(96.61)	(5.09)	(5.09)	(5.09)
LIQ_SPR	0***	0***	0***	0	0	0	-1.41***	-1.41***	-1.41***
	(3.05)	(3.04)	(-6.21)	(-.01)	(-.01)	(-.01)	(-9.82)	(-9.82)	(-9.82)
TED_SPR	0***	0***	0***	0***	0***	0***	-0.14***	-1.44***	-1.43***
	(4.28)	(4.27)	(-4.45)	(18.03)	(18.03)	(18.03)	(-12.94)	(-12.94)	(-12.94)
_cons	0***	0***	0	-.01***	-.01***	-.01***	-36.28***	-36.28***	-36.28***
	(33.58)	(5.35)	(-.4)	(-23.75)	(-10.48)	(-10.32)	(-41.87)	(-13.5)	(-14.06)
Observations	50327	50327	50327	50327	50327	50327	50327	50327	50327
R-squared	.1	.1	.z	.59	.59	.z	.17	.17	.z

Note: t-values are in parentheses. For SRISK, coefficients are in exponent xe05.
*** p<.01, ** p<.05, * p<.1.

Table 7.10. Hausman Specification Test

DCoVaR	Coef.
Chi-square test value	24.406
P-value	.002
MES	**Coef.**
Chi-square test value	1.089
P-value	.993
SRISK	**Coef.**
Chi-square test value	.027
P-value	1

Table 7.11. Breusch Pagan Test

Breusch and Pagan Lagrangian multiplier test for random effects

DCOVAR[ID,t] = Xb + u[ID] + e[ID,t]

Estimated results:

	Var	SD = sqrt(Var)
DCOVAR	6.32e-13	7.95e-07
E	4.83e-14	2.20e-07
u	1.34e-13	3.66e-07

Test: Var(u) = 0

chibar2(01) = 2.1e+07

Prob > = 0.0000

As proven by the Breusch Pagan Lagrangian test, we should run the pooled OLS for the ΔCoVaR. To choose the robust model, the first step is to check that the assumptions of OLS hold. Stata results detect heteroscedasticity, autocorrelation and non-normal distribution of error terms. To fix these problems, we fit ARCH(1) and GARCH(1) models to avoid bias on estimation. The test of OLS assumptions is available in the robustness tests at the end of this chapter.

The ARCH model was introduced by Engle (1982) in his study of UK inflation. It assumed heteroscedasticity in autoregression, where the current value depends on its past and conditional. ARCH allows the conditional variance to change over time, and to understand the ARCH model, we can think of AR(1) process described as $y_t = \varnothing_0 + \varnothing_1 y_{t-1} + \varepsilon_t \quad |\varnothing_1| < 1$, where ε_t is white noise with $Var(\varepsilon_t) \equiv \sigma^2_\varepsilon$. In this assumption, the variance is constant. This assumption is relaxed by the ARCH process, as follows:

$$Var(y_t) = Var(\varnothing_0 + \varnothing_1 y_{t-1} + \varepsilon_t)$$
$$= \varnothing^2_1 Var(y_{t-1}) + Var(\varepsilon_t)$$

$\sigma^2_y = \varnothing^2_1\sigma^2_y + \sigma^2_\varepsilon$

where $Var(y_t) = Var(y_{t-1}) \equiv \sigma^2_y$ and $Var(\varepsilon_t) = \sigma^2_\varepsilon$. Therefore:

$(1-\varnothing^2_1)\sigma^2_y = \sigma^2_\varepsilon$, hence we can arrive at the unconditional variance of y_t :

$\sigma^2_y = \sigma^2_\varepsilon/(1-\varnothing^2_1)$

The basics of the ARCH model are as follows:

$$y_t = u_t\sigma_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_t^2{}_{-1}$$

where:

(i) $\alpha_0 \geq 0$ and if $\alpha_1 = 0$ then the conditional variance α_0 and non-negative or positive.

(ii) if $\alpha_1 \geq 0$ the $y_t^2{}_{-1}$ will be non-negative.

(iii) when the $\alpha_1 > 0$ the conditional variance of y_t will increase because of $y_t^2{}_{-1}$.

(iv) $\alpha_1 < 1$ the process is not covariance stationary.

(v) $3\sigma^2_1 < 1$ for finite fourth moment.

Therefore, the ARCH(q) process then can be modelled as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_t^2{}_{-1} + \ldots + \alpha_q y_t^2{}_{-q} = \alpha_0 + \sum_{i=1}^{q} y_{t-1}^2$$

The ARCH(1) model was developed further by Bollerslev (1986), who introduced generalised ARCH (GARCH) by adding a lagged variance term to the conditional variance. GARCH is practical for estimating persistent movements in volatility without the condition of counting on a large number of coefficients in a high order polynomial. The GARCH model is:

$$\sigma^2_t = \alpha_0 + \alpha_1 y^2_{t-1} + \beta_1\sigma^2_{t-1}$$

GARCH(p,q), where p is the lag of σ^2_t and q represent the lag of y^2_t, with $p = 1$ and $q = 1$. The following condition exploits such conditional variance as non-negative and $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$. GARCH is popular in financial modelling because it gives the outcome with only four parameters. It also explains the stylised fact daily returns and volatility forecast accuracy as achieved by using more complex models. GARCH's superiority is supported by Hansen and Lunde (2005) in their study comparing the performance of 330 ARCH-type models using DM - $ exchange rate data and daily IBM return data. They found that the GARCH(1,1) process provides better estimation of volatility for financial time series compared to other ARCH family models (such as IGARCH, A-GARCH, NA-GARCH, V-GARCH, EGARCH, A-PARCH and GJR-GARCH). The estimation results of ARCH(1,1) and GARCH(1,1) models are presented in Table 7.12.

Table 7.12. CoVaR ARCH(1,1) and GARCH(1,1)

Delta_CoVaR	Coef.	Std.err.	t-value	p-value	[95% Conf	Interval]
Delta_CoVaR						
DCovar_1	-15697.014	2877.322	-5.46	0	-21336.462	-10057.566
Beta	88.335	12.162	7.26	0	64.498	112.171
Exch_Rate	.069	.002	33.07	0	.065	.073
FFR	-59.711	4.458	-13.39	0	-68.448	-50.974
TBILL_DELTA	.648	.156	4.14	0	.341	.954
JKSE_VIX	1.421	.21	6.75	0	1.009	1.834
LIQUIDITY_SPREAD	19.918	6.29	3.17	.002	7.589	32.247
TED_SPREAD	7.812	2.941	2.66	.008	2.048	13.576
Constant	237.717	30.951	7.68	0	177.054	298.381
ARCH						
arch						
L1	.047	.012	3.96	0	.023	.07
garch						
L1	.955	.011	85.70	0	.933	.976
Constant	8.457	9.509	0.89	.374	-10.18	27.095

To consider the effects of unobserved variables on the independent variable in ΔCoVaR, MES and SRISK estimations, the extended analysis incorporates the finite mixture model (FFM). A summary of FMM class 1 and class 2 means difference analysis for ΔCoVaR and MES is presented in Table 7.13. For SRISK, FMM fails to achieve convergence and so the model is not considered.

Table 7.13. Latent Class Marginal Means

	Coefficient	Std. err.	t-value	p-value	[95% Conf	Interval]
DCOVAR	2.82E-07	1.83E-09	153.92	0	2.78E-07	2.86E-07
DCOVAR	1.08E-06	1.18E-08	91.64	0	1.05E-06	1.10E-06

	Coefficient	Std. err.	t-value	p-value	[95% Conf	Interval]
MES	0.0129582	0.0000196	662.66	0	0.0129199	0.0129966
MES	0.0173357	0.0000992	174.72	0	0.0171413	0.0175302

Based on the regression overall output, the outcomes can be summarised as follows:

1. Beta and market index volatility: stock beta has positive correlation and is statistically significant to systemic risk in all market model estimations. In this case, bank systemic risk swings downward or upward in the same direction of the overall market. This result is also confirmed when we apply market index volatility. Using

simple beta to assess SIBs is suggested by Benoit, Colletaz and Hurlin (2011). The results agree with our assessments in Chapters 5 and 6, where we detected the co-movement of asset returns using PCA and granger network causality.

2. Exchange rate: Fluctuation of exchange rate could trigger and amplifies systemic risk. Its effects are validated as statistically significant by the linear and ARCH models. This finding aligns with Yesin (2013), Mayordomo, Rodriguez-Moreno and Peña (2014) and de Mendonça and Silva (2018) but is contrary to Tram and Thi Thanh Hoai (2021). The shocks of exchange rate volatility influence banks' assets and liabilities, especially when there is no hedging or insurance to cover the risk. The 1997 Asian financial crisis, where Indonesia was one of the severely hit economies, is a good example of the catastrophic effect of exchange rate on the banking system.
3. Central bank funding and T-bill rate: The outcome of these is statistically significant, though the effect is mixed between estimation models. CoVaR and MES report the negative effect of FFR to systemic risk, while SRISK reports the opposite. We suspect that SRISK methodology, which considers leverage, affects the outcome when banks' assets are sensitive to monetary policy interest rate changes—a phenomenon studied by Jobst (2014) and Brunnermeier and Pedersen (2009). When we assess the delta of three-month T-bill, the implication is the same across all models. This could indicate that the sample banks are more sensitive to the FFR than the three-month T-bill rate, as the former resembles the overnight money market of short-term liquidity resort. Ramos-Tallada (2015) also iterated the sensitivity of banks to short-term interest rates and potential losses during times of tight monetary policy.
4. Liquidity spread: In general, liquidity spread is not significant to banks' systemic risk exposure. Since we use the three-month repo rate, the non-significance could be due to the very limited repo transactions in the Indonesian banking sector. However, the effect could be different for other countries, as it very much depends on banks' portfolios. Conversely, TED spread results are quite mixed among the models. CoVaR detects a negative relation to systemic risk, in line with Ramos-Tallada (2015), while MES and SRISK detect a positive relation to systematic risk, in line with Laséen, Pescatori and Turunen (2017). Further research to explore the effect of the SRISK model on benchmark rate is appealing, as it is arguably in line with the central bank funding rate.

7.4.4 Technical Integration

The BCBS (2018) indicator-based approach uses the categories of institution size, interconnectedness, substitutability, global cross-jurisdictional activity and complexity, giving equal weighting to these five categories. BCBS allows some departure from the BCBS (2012) guideline for domestic regulators to better capture specific D-SIBs characteristics and country externalities. OJK has adjusted the formulae composition, as detailed in POJK No. 2/POJK.03/2018 (OJK 2018). The SIB assessment indicators after this adjustment are shown in Table 7.14.

Table 7.14. Basel and Adjusted Indicators

BCBS (2018) Indicators			**OJK (2018) Adjusted Indicators**		
Category (weighting)	*BCBS G-SIBs*	*Indicator weighting*	*Category (weighting)*	*Adjusted indicators D-SIBs*	*Indicator weighting*
Size (20%)	Total exposures	20%	Size (33.3%)	Total exposures	100%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Interconnectedness (33.3%)	Intra-financial system assets	33.3%
	Intra-financial system liabilities	6.67%		Intra-financial system liabilities	33.3%
	Securities outstanding	6.67%		Securities outstanding	33.3%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	Complexity (33.3%)	Notional amount of over-the-counter (OTC) derivatives	25%
	Level 3 assets	6.67%		Trading and available-for-sale securities	25%
	Trading and available for sale securities	6.67%		Domestic indicators	25%
				Substitutability (payment system and custodian)	25%
Substitutability (20%)	Assets under custody	6.67%			
	Payment activity	6.67%			
	Underwritten transactions in debt and equity markets	3.33%			

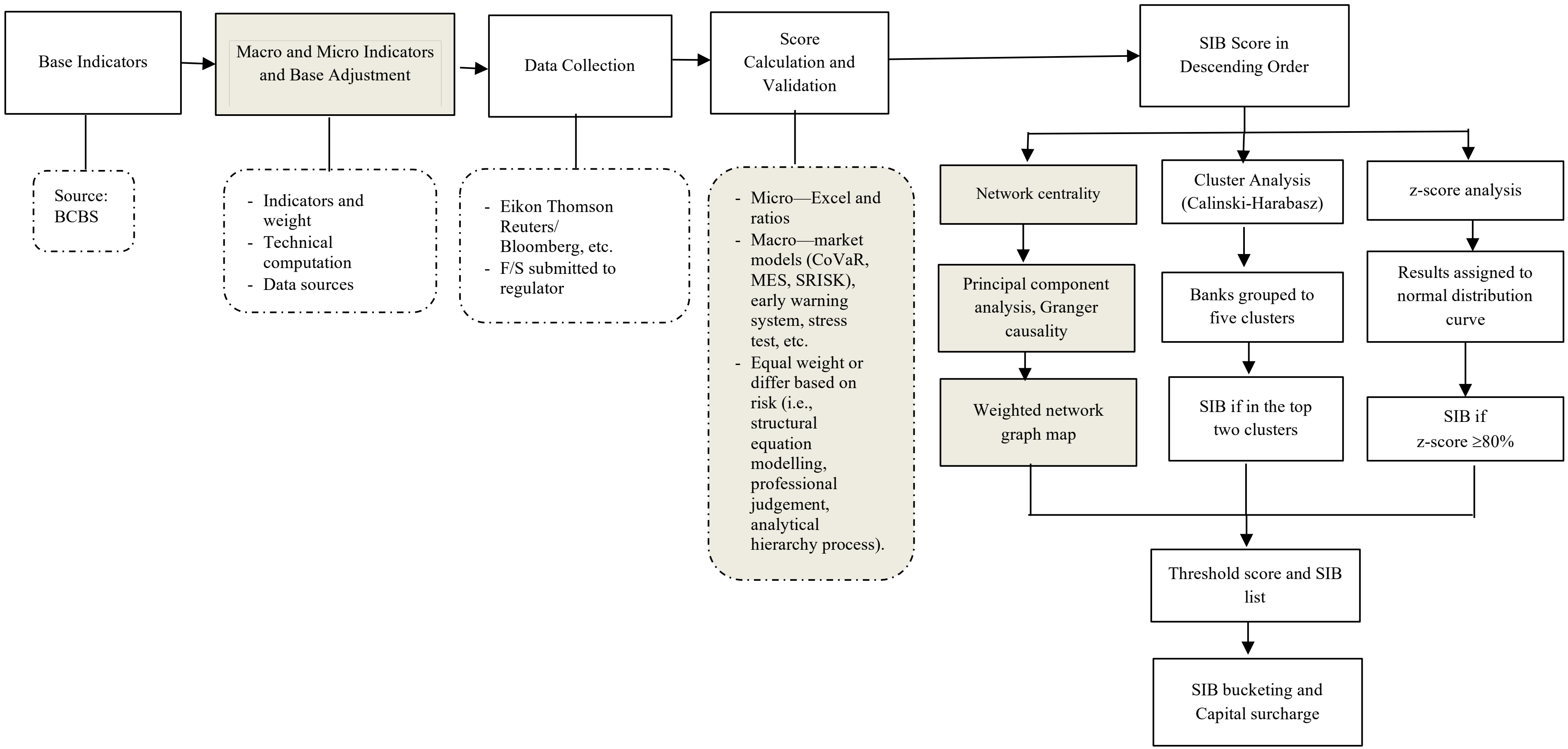
	Trading volume	3.33%
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%

Source: OJK (2018).

We aim to provide a practical assessment framework and possible technical indicators to integrate the effects of macroeconomic shocks into SIB assessment. The developed framework is presented in Figure 7.1. A country-specific design is permitted by BCBS and important for providing holistic supervision analysis to mitigate future systemic risk (BCBS 2012). We use Indonesian banks as our sample, but regulatory authorities in any country could replicate the tools for non-bank financial institutions, albeit adjusted to suit industry- and country-specific characteristics. The framework was derived from the BCBS (2018) base model and then developed using a combination of macroeconomic and micro bank granular data. During the preliminary steps, the researcher and their supervisors discussed which variables or ratios to use that represented both aspects, allocating weight to each variable, as well as the technical computation methods and data source. Country-specific reading was undertaken, for example, Brämer and Gischer (2013) when determining suggestions for Australian D-SIBs; Bengtsson, Holmberg and Jonsson (2013) for Swedish banks; and Glasserman and Loudis' (2015) report comparing US D-SIBs and international G-SIBs.

The third step involved the data collection process, which required decision on which statistics to gather. We sourced information from internal sources (e.g., financial reports) and external databases. After data collection, the process continued for analysis and technical calculation. For thorough assessment, we proposed integration of the market model approach to complement and validate the SIB shortlist based on Basel guideline. Choice of market model could be developed further to suit individual policymaker's needs. The weight for each ratio or parameter could be attributed equally or based on a method such as a structural equation model, professional judgement and survey, or combination. The last step in the framework was to group the banks or financial institutions based on the analysis. The methods of segregation are adjustable and can act as validation tools of comparison. The full framework is presented in Figure 7.1.

Figure 7.1. Assessment Framework Workflow



Source: Adapted from OJK (2018).

To put the assessment framework into practice, we also suggest adding some ratios and parameters to reflect the integration of macro and micro data into SIB assessment (see Table 7.15). Review of methodology is encouraged at least once every three years (BCBS 2018). The proposed ratios represent macroeconomic shocks in line with our previous regression results:

- Currency exposures—incorporates an entity's exposure to unfavourable currency movements (i.e., unhedged liabilities to total liabilities). Indonesia experienced high currency volatility during the 1997 Asian financial crisis after the shift from a pegged currency system to a floating system. Currently, the central bank imposes mandatory hedging as a portion of foreign liabilities; however, there is still some exposure to sudden shocks.
- Market volatility—stock beta, marked-to-market securities per total securities in portfolio, T-bills and T-bonds to total securities. This ratio acknowledges the effect of market volatility that could potentially harm financial institutions. We also consider government bonds as a risky investment, considering, for example, the Eurozone sovereign debt crisis of 2010–2011. Paltalidis et al. (2015) provide evidence of the sovereign credit channel as one systemic risk transmission channel.
- Policies exposure—delta of future incomes or liabilities as consequences of change in the policy interest rate. The ratios aim to capture entity fragility stemming from government regulations or policymaker decisions—for example, change in risk-free anchor rate, people mobility restrictions affecting business during the COVID-19 pandemic, administered price, etc.

7.5 Conclusion and Policy Implications

This chapter investigated how macroeconomic shocks could affect systemic risk through several transmission channels. To explore macroeconomic variables' connection to systemic risk, we employed three market models—CoVaR (Adrian & Brunnermeier 2016), MES (Acharya, Engle & Richardson 2012) and SRISK (Brownlees & Engle 2017)—using the adjusted linear equation from de Mendonça and Silva (2018) and expanding on its analysis by employing fixed effects, random effects, ARCH and GARCH models. To consider the unobserved groups of variables that could affect the independent variables, we fit FMM. Our findings show that stock beta, market index volatility and exchange rate volatility amplify transmission of systemic risk. These results align with our findings in Chapters 5 and 6 regarding the co-movement of asset returns. In addition, change in anchor interest rate by a policymaker is proven to be significant, but the effect varies among the market models. The difference could stem from the models' employed variables and differences in interest rate time horizon. The effect of liquidity spread varies among the models. Further research to explore the effects of certain model variables and financial market deepness on the outcome is recommended.

Finally, we proposed some practical improvements for the SIB assessment framework to better capture potential macroeconomic shocks. We also suggested technical integration calculations and ratios that reflect the added steps. The integrated macro and micro granular data could portray overall risk endogenously and externally expose SIFIs.

Table 7.15. SIB Assessment Technical Integration

Category (weighting)	BCBS G-SIBs	Indicator weighting	Category (weighting)	POJK No. 2/POJK.03/2018 Indicators D-SIBs	Indicator weighting	Category (weighting)	Macro to micro indicators D-SIBs	Indicator weighting
Size (20%)	Total exposures	20%	Size (33.3%)	Total exposures	100%	Size (25%)	Total exposures	100%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Interconnectedness (33.3%)	Intra-financial system assets	33.3%	Interconnectedness (25%)	Intra-financial system assets	33.3%
	Intra-financial system liabilities	6.67%		Intra-financial system liabilities	33.3%		Intra-financial system liabilities	33.3%
	Securities outstanding	6.67%		Securities outstanding	33.3%		Securities outstanding	33.3%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	Complexity (33.3%)	Notional amount of over-the-counter (OTC) derivatives	25%	Complexity (25%)	Notional amount of over-the-counter (OTC) derivatives	25%
	Level 3 assets	6.67%		Trading and available-for-sale securities	25%		Trading and available-for-sale securities	25%
	Trading and available for sale securities	6.67%		Domestic indicators	25%		Domestic indicators	25%
				Substitutability (payment system & custodian)	25%		Substitutability (payment system & custodian)	25%
Substitutability (20%)	Assets under custody	6.67%				Macroeconomic shocks (25%)	Currency exposure	33.3%
	Payment activity	6.67%					Market volatility	33.3%
	Underwritten transactions in debt & equity markets	3.33%					Policies exposure	33.3%
	Trading volume	3.33%						
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%						
	Cross-jurisdictional liabilities	10%						

Note: Additional indicators shaded grey.
Source: Adapted from BCBS (2018) and OJK (2018).

A. Robustness Test

1. Random Effects

GLS regression DCoVaR

DCOVAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
DCOVAR_1	1.43E-07	5.99E-09	23.96	0	1.32E-07	1.55E-07	***
Beta	1.71E-07	3.07E-09	55.62	0	1.65E-07	1.77E-07	***
EXC_RATE	-3.56E-12	7.05E-13	-5.05	0	-4.95E-12	-2.18E-12	***
FFR	7.49E-10	1.56E-09	0.48	.631	-2.31E-09	3.80E-09	
TBILL_DELTA	2.99E-09	9.77E-11	30.59	0	2.80E-09	3.18E-09	***
JKSE_VIX	5.84E-09	1.25E-10	46.87	0	5.59E-09	6.08E-09	***
LIQ_SPR	5.75E-09	1.89E-09	3.04	.002	2.05E-09	9.46E-09	***
TED_SPR	6.25E-09	1.46E-09	4.27	0	3.38E-09	9.12E-09	***
Constant	3.83E-07	7.15E-08	5.35	0	2.43E-07	5.23E-07	***

Mean dependent var	0.000	SD dependent var	0.000
Overall r-squared	0.400	Number of obs	50327
Chi-square	.	Prob > chi2	.
R-squared within	0.104	R-squared between	0.666

*** p<.01, ** p<.05, * p<.1.

ML regression DCoVaR

DCOVAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
DCOVAR_1	-6.37E-09	9.05E-09	-0.70	.482	-2.41E-08	1.14E-08	
Beta	9.57E-07	.	.	.	.	.	
EXC_RATE	-1.44E-11	1.07E-12	-13.46	0	-1.65E-11	-1.23E-11	***
FFR	2.10E-08	2.36E-09	8.86	0	1.63E-08	2.56E-08	***
TBILL_DELTA	4.95E-09	1.48E-10	33.44	0	4.66E-09	5.24E-09	***
JKSE_VIX	9.76E-09	1.88E-10	52.02	0	9.40E-09	1.01E-08	***
LIQ_SPR	-1.78E-08	2.87E-09	-6.21	0	-2.34E-08	-1.22E-08	***
TED_SPR	-9.86E-09	2.22E-09	-4.45	0	-1.42E-08	-5.51E-09	***
Constant	-3.70E-08	9.24E-08	-0.40	.689	-2.18E-07	1.44E-07	

Mean dependent var	0.000	SD dependent var	0.000
Pseudo r-squared	0.026	Number of obs	50327
Chi-square	-36541.301	Prob > chi2	1.000
Akaike crit. (AIC)	-1357894.015	Bayesian crit. (BIC)	-1357832.231

*** p<.01, ** p<.05, * p<.1

GLS Regression MES

MES	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MES_1	0.000096	0.0000173	5.56	0	0.0000622	0.0001299	***
Beta	0.0152966	0.0000601	254.34	0	0.0151788	0.0154145	***
EXC_RATE	2.33E-07	1.39E-08	16.74	0	2.05E-07	2.60E-07	***
FFR	0.0002983	0.0000307	9.70	0	0.000238	0.0003586	***
TBILL_DELTA	0.0001225	1.93E-06	63.62	0	0.0001188	0.0001263	***
JKSE_VIX	0.0002372	2.46E-06	96.60	0	0.0002324	0.000242	***
LIQ_SPR	-2.82E-07	0.0000373	-0.01	.994	-0.0000733	0.0000728	
TED_SPR	0.0005198	0.0000288	18.03	0	0.0004633	0.0005763	***
Constant	-0.0053431	0.0005096	-10.48	0	-0.0063419	-0.0043443	***

Mean dependent var	0.014	SD dependent var	0.010
Overall r-squared	0.766	Number of obs	50327
Chi-square	73223.680	Prob > chi2	0.000
R-squared within	0.592	R-squared between	0.901

*** p<.01, ** p<.05, * p<.1

ML Regression MES

MES	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MES_1	0.000096	0.0000173	5.56	0	0.0000622	0.0001299	***
Beta	0.0152966	0.0000601	254.35	0	0.0151787	0.0154145	***
EXC_RATE	2.33E-07	1.39E-08	16.74	0	2.05E-07	2.60E-07	***
FFR	0.0002983	0.0000307	9.70	0	0.000238	0.0003585	***
TBILL_DELTA	0.0001225	1.93E-06	63.63	0	0.0001188	0.0001263	***
JKSE_VIX	0.0002372	2.46E-06	96.61	0	0.0002324	0.000242	***
LIQ_SPR	-2.81E-07	0.0000373	-0.01	.994	-0.0000733	0.0000728	
TED_SPR	0.0005198	0.0000288	18.03	0	0.0004633	0.0005763	***
Constant	-0.0053431	0.0005177	-10.32	0	-0.0063577	-0.0043285	***

Mean dependent var	0.014	SD dependent var	0.010
Pseudo r-squared	-0.126	Number of obs	50327
Chi-square	45155.546	Prob > chi2	0.000
Akaike crit. (AIC)	-404605.826	Bayesian crit. (BIC)	-404508.737

*** p<.01, ** p<.05, * p<.1

GLS Regression SRISK

SRISK	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SRISK_1	-1137.925	1595.72	-0.71	.476	-4265.478	1989.629	
Beta	2049893.2	23158.48	88.52	0	2004503.4	2095283	***
EXC_RATE	208.682	5.354	38.97	0	198.188	219.176	***
FFR	190879.94	11838.344	16.12	0	167677.21	214082.67	***
TBILL_DELTA	2430.763	741.665	3.28	.001	977.126	3884.4	***
JKSE_VIX	4811.811	945.5	5.09	0	2958.665	6664.957	***
LIQ_SPR	-140933.72	14353.475	-9.82	0	-169066.01	-112801.42	***
TED_SPR	-143602.27	11101.53	-12.94	0	-165360.87	-121843.67	***
Constant	-3627708.7	268653.52	-13.50	0	-4154259.9	-3101157.5	***

Mean dependent var	732175.737	SD dependent var	2411476.606
Overall r-squared	0.246	Number of obs	50327
Chi-square	10226.070	Prob > chi2	0.000
R-squared within	0.169	R-squared between	0.352

*** p<.01, ** p<.05, * p<.1

ML regression SRISK

SRISK	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SRISK_1	-1137.835	1595.614	-0.71	.476	-4265.181	1989.511	
Beta	2049881.4	23154.958	88.53	0	2004498.6	2095264.3	***
EXC_RATE	208.682	5.354	38.98	0	198.188	219.176	***
FFR	190879.64	11837.556	16.12	0	167678.46	214080.82	***
TBILL_DELTA	2430.734	741.616	3.28	.001	977.194	3884.274	***
JKSE_VIX	4811.752	945.436	5.09	0	2958.731	6664.773	***
LIQ_SPR	-140933.37	14352.519	-9.82	0	-169063.79	-112802.95	***
TED_SPR	-143602.03	11100.791	-12.94	0	-165359.18	-121844.88	***
Constant	-3627702.4	257958.6	-14.06	0	-4133292	-3122112.8	***

Mean dependent var	732175.737	SD dependent var	2411476.606
Pseudo r-squared	0.006	Number of obs	50327
Chi-square	9310.685	Prob > chi2	0.000
Akaike crit. (AIC)	1585238.093	Bayesian crit. (BIC)	1585335.182

*** p<.01, ** p<.05, * p<.1

2. Fixed Effects

DCoVaR

DCOVAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
DCOVAR_1	1.44E-07	5.98E-09	23.99	0	1.32E-07	1.55E-07	***
Beta	1.70E-07	3.07E-09	55.49	0	1.64E-07	1.76E-07	***
EXC_RATE	-3.56E-12	7.05E-13	-5.05	0	-4.94E-12	-2.18E-12	***
FFR	7.37E-10	1.56E-09	0.47	.636	-2.32E-09	3.79E-09	
TBILL_DELTA	2.99E-09	9.76E-11	30.60	0	2.80E-09	3.18E-09	***
JKSE_VIX	5.83E-09	1.24E-10	46.88	0	5.59E-09	6.08E-09	***
LIQ_SPR	5.77E-09	1.89E-09	3.05	.002	2.06E-09	9.47E-09	***
TED_SPR	6.26E-09	1.46E-09	4.28	0	3.40E-09	9.12E-09	***
Constant	3.83E-07	1.14E-08	33.58	0	3.61E-07	4.05E-07	***

Mean dependent var	0.000	SD dependent var	0.000
R-squared	0.104	Number of obs	50327
F-test	731.767	Prob > F	0.000
Akaike crit. (AIC)	-1400273.306	Bayesian crit. (BIC)	-1400220.348

*** p<.01, ** p<.05, * p<.1

MES

MES	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MES_1	0.0000173	5.56	5.56	0	0.0000623	0.00013	***
Beta	0.0152957	0.0000603	253.85	0	0.0151776	0.0154138	***
EXC_RATE	2.33E-07	1.39E-08	16.74	0	2.05E-07	2.60E-07	***
FFR	0.0002983	0.0000307	9.70	0	0.000238	0.0003585	***
TBILL_DELTA	0.0001225	1.93E-06	63.62	0	0.0001188	0.0001263	***
JKSE_VIX	0.0002372	2.46E-06	96.60	0	0.0002324	0.000242	***
LIQ_SPR	-2.52E-07	0.0000373	-0.01	.995	-0.0000733	0.0000728	
TED_SPR	0.0005199	0.0000288	18.03	0	0.0004634	0.0005764	***
Constant	-0.0053426	0.000225	-23.75	0	-0.0057835	-0.0049016	***

Mean dependent var	0.014	SD dependent var	0.010
R-squared	0.592	Number of obs	50327
F-test	9121.546	Prob > F	0.000
Akaike crit. (AIC)	-404808.759	Bayesian crit. (BIC)	-404729.322

*** p<.01, ** p<.05, * p<.1

Fixed Effects Regression

SRISK	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SRISK_1	-1138.863	1595.742	-0.71	.475	-4266.535	1988.808	
Beta	2050016.9	23179.989	88.44	0	2004583.9	2095449.9	***
EXC_RATE	208.68	5.354	38.97	0	198.185	219.175	***
FFR	190883.12	11838.531	16.12	0	167679.47	214086.77	***
TBILL_DELTA	2431.072	741.679	3.28	.001	977.372	3884.771	***
JKSE_VIX	4812.43	945.526	5.09	0	2959.189	6665.672	***
LIQ_SPR	-140937.36	14353.698	-9.82	0	-169070.77	-112803.95	***
TED_SPR	-143604.82	11101.698	-12.94	0	-165364.27	-121845.37	***
Constant	-3627747	86633.759	-41.87	0	-3797550.2	-3457943.9	***

Mean dependent var	732175.737	SD dependent var	2411476.606
R-squared	0.169	Number of obs	50327
F-test	1276.552	Prob > F	0.000
Akaike crit. (AIC)	1585018.841	Bayesian crit. (BIC)	1585098.278

*** p<.01, ** p<.05, * p<.1

3. Finite Mixture Model

Finite mixture model

	Coefficient	Std. err.	t-value	p-value	[95% Conf	Interval]
1. Class	(base outcome)					
2. Class						
_cons	-.9254955	.0157976	-58.58	0	-0.9564583	-0.8945327

Class: 1
Response: DCOVAR
Model: regress

DCOVAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
DCOVAR_1	-5.26E-	1.11E-08	-4.75	0	-7.44E-08	-3.09E-08	***
Beta	4.74E-07	4.48E-09	105.73	0	4.65E-07	4.83E-07	***
EXC_RATE	-3.26E-	8.43E-13	-3.86	0	-4.91E-12	-1.61E-12	***
FFR	8.16E-09	2.02E-09	4.04	0	4.20E-09	1.21E-08	
TBILL_DELTA	5.57E-10	1.23E-10	4.52	0	3.15E-10	7.98E-10	***
JKSE_VIX	1.09E-09	1.59E-10	6.9	0	7.83E-10	1.40E-09	***
LIQ_SPR	6.77E-09	2.33E-09	2.91	.004	2.21E-09	1.13E-08	***
TED_SPR	2.97E-09	1.89E-09	1.57	.116	-7.34E-10	6.67E-09	***
Constant	-5.78E-	1.38E-08	-4.2	0	-8.48E-08	-3.08E-08	***
Var(e.DCOVAR)	4.01e-14	4.36e-16			3.93e-14	4.10e-14	

Class: 2
Response: DCOVAR
Model: regress

DCOVAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
DCOVAR_1	-2.52e-	3.59e-08	-0.70	.482	-9.55E-08	- 4.51E-08	***
Beta	7.95E-07	1.13E-08	70.42	0	7.73E-07	8.17E-07	***
EXC_RATE	-7.34E-	6.05E-12	-12.14	0	-8.53E-11	-6.16E-11	***
FFR	7.65E-08	1.21E-08	6.31	0	5.28E-08	1.00E-07	
TBILL_DELTA	9.40E-09	7.37E-10	12.76	0	7.96E-09	1.08E-08	***
JKSE_VIX	1.86E-08	9.37E-10	19.84	0	1.68E-08	2.04E-08	***
LIQ_SPR	-7.65E-	1.49E-08	-5.13	0	-1.06E-07	-4.73E-08	***
TED_SPR	-7.62E-	1.12E-08	-6.78	0	-9.83E-08	-5.42E-08	***
Constant	1.29E-06	9.75E-08	13.23	0	1.10E-06	1.48E-06	***
Var(e.DCOVAR)	6.53e-13	8.72e-15			6.36e-13	6.70e-13	

Finite mixture model

	Coefficient	Std. err.	t-value	p-value	[95% Conf	Interval]
1. Class	(base outcome)					
2. Class						
_cons	-.9254955	.0157976	-58.58	0	-0.9564583	-0.8945327

Class: 1
Response: MES
Model: regress

MES	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MES_1	0.000018	9.47E-06	-2	0.046	-0.0000375	-3.53E-07	***
Beta	0.015767	0.000040	385.89	0	0.015687	0.0158472	***
EXC_RATE	1.56E-07	1.00E-08	15.54	0	1.36E-07	1.76E-07	***
FFR	3.41E-04	0.000022	14.96	0	2.97E-04	0.0003861	
TBILL_DELTA	5.89E-05	1.59E-06	37.02	0	5.58E-05	0.000062	***
JKSE_VIX	1.15E-04	2.07E-06	55.49	0	1.11E-04	0.0001191	***
LIQ_SPR	2.92E-04	0.000027	10.78	0	2.39E-04	0.0003447	***
TED_SPR	-1.05E-	0.000022	-0.48	.634	-5.37E-05	0.0000327	***
Constant	-2.58E-	0.000167	-15.43	0	-2.91E-03	-0.0022508	***
Var(e.MES)	5.41e-06	7.51e-08			5.27e-06	5.56e-06	

Class: 2
Response: MES
Model: regress

MES	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MES_1	2.06E-03	0.000178	11.54	0	1.71E-03	0.0024094	***
Beta	0.0123112	0.000120	102.04	0	0.0120747	0.0125476	***
EXC_RATE	4.17E-07	5.45E-08	7.65	0	3.10E-07	5.24E-07	***
FFR	0.0007349	0.000121	6.03	0	0.0004962	0.0009736	
TBILL_DELTA	0.0002208	6.72E-06	32.87	0	0.0002077	0.000234	***
JKSE_VIX	0.0004296	8.75E-06	49.12	0	0.0004125	0.0004468	***
LIQ_SPR	0.0001856	0.000153	1.21	.225	-0.0001144	0.0004856	***
TED_SPR	0.0013396	0.000109	12.22	0	0.0011248	0.0015544	***
Constant	-0.0109833	0.000873	-12.58	0	-0.0126943	-0.0092723	***
Var(e.MES)	.000059	9.50e-07			.0000572	.0000609	

Finite mixture model

	Coefficient	Std. err.	t-value	p-value	[95% Conf	Interval]
1. Class	(base outcome)					
2. Class						
_cons	1.029225	.0101348	101.55	0	1.009361	1.049089

Class: 1
Response: SRISK
Model: regress

SRISK	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SRISK_1	-	5.24E+0	-4.08	0	-3.17E+04	-1.11E+04	***
Beta	4.20E+0	3.53E+0	119.1	0	4.13E+06	4.27E+06	***
EXC_RATE	7.28E+0	1.94E+0	37.54	0	6.90E+02	7.66E+02	***
FFR	5.57E+0	3.45E+0	16.13	0	4.90E+05	6.25E+05	
TBILL_DELTA	4.91E+0	2.38E+0	2.06	0.039	2.49E+02	9.57E+03	***
JKSE_VIX	1.10E+0	3.05E+0	3.6	0	4.99E+03	1.70E+04	***
LIQ_SPR	-	4.34E+0	-16.25	0	-7.90E+05	-6.20E+05	***
TED_SPR	-	33964.61	-15.22	0	-583433.9	-450295	***
Constant	-	308257.6	-33.74	0	-1.10E+07	-9796600	***

Class: 2
Response: SRISK
Model: regress

SRISK	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SRISK_1	244.1052	2.998408	81.41	0	238.2284	249.9819	***
Beta	368.4873	27.96307	13.18	0	313.6807	423.2939	***
EXC_RATE	1.60E+00	9.91E-03	161.98	0	1.59E+00	1.62E+00	***
FFR	2.53E+03	23.27989	108.74	0	2485.733	2576.989	
TBILL_DELTA	7.58E+00	1.41E+0	5.39	0	4.82E+00	1.03E+01	***
JKSE_VIX	1.53E+01	1.78E+0	8.59	0	1.18E+01	1.88E+01	***
LIQ_SPR	-2.02E+03	2.79E+0	-72.45	0	-2.07E+03	-1.96E+03	***
TED_SPR	-9.24E+02	2.16E+0	-42.75	0	-9.66E+02	-8.81E+02	***
Constant	-2.97E+04	1.61E+0	-184.29	0	-3.00E+04	-2.93E+04	***
	244.1052	2.998408	81.41	0	238.2284	249.9819	

4. Heteroscedasticity of Pooled OLS

Breusch–Pagan/Cook–Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of Delta_CoVaR

H0: Constant variance

chi2(1) = 19.08
Prob > chi2 = 0.0000

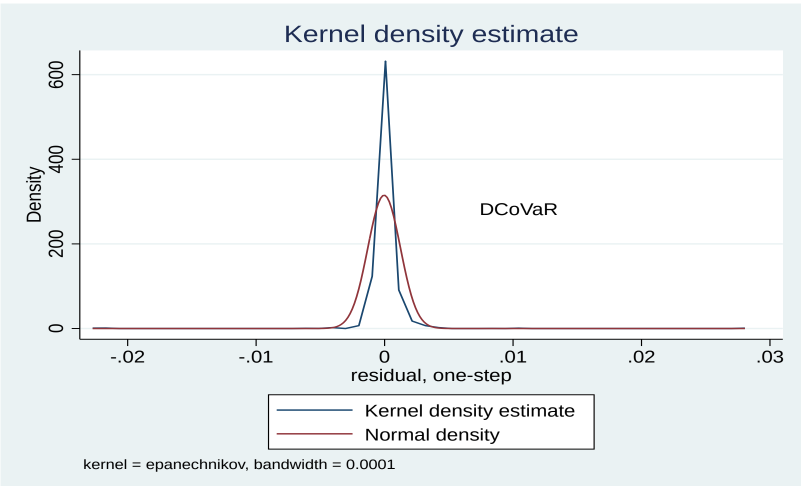
5. Autocorrelation of error terms

Breusch-Godfrey LM test for autocorrelation - ΔCoVaR

Lags(p)	chi2	df	Prob > chi2
1	479.55	1	0.0000

Ho: no serial correlation

6. Test of normal distribution



7. ARIMA (1,0,1) - ΔCoVaR

Using ARIMA (1,0,1), both AR(1) and MA(1) are statistically significant and indicate linear correlation or autocorrelation.

DCovar_1	Coef.	St.Err.	t-value	p-value	[95%	Interval]	Sig
DCovar_1							
_cons	.008	.008	1.09	.277	-.007	.023	
ARMA							
ar							
L1.	.999	.001	1773.1	0	.998	1	***
ma.							
L1.	-.639	.003	-223.91	0	-.644	-.633	***
Constant							
/sigma	.001	0	500.40	0	.001	.001	***

*** p<.01, ** p<.05, * p<.1

We run another test using correlogram and partial auto correlogram to further investigate the fitness of the AR and MA models for ΔCoVaR. The results confirm the ARIMA (1,0,1) result that autocorrelation exists.

```
                                          -1       0       1 -1       0       1
 LAG       AC       PAC       Q     Prob>Q  [Autocorrelation]  [Partial autocor]
-------------------------------------------------------------------------------
1       -0.0374  -0.0381   4.1471  0.0417
2        0.0715   0.0802   19.328  0.0001
3       -0.0416  -0.0488   24.477  0.0000
4       -0.0536  -0.0769   33.021  0.0000
5       -0.0938  -0.1109    59.17  0.0000
6       -0.0315  -0.0463   62.118  0.0000
7       -0.0161  -0.0300   62.893  0.0000
8        0.0919   0.0907   88.019  0.0000
9        0.1099   0.1311   124.02  0.0000
10      -0.0015   0.0369   124.03  0.0000
11      -0.0247  -0.0091   125.84  0.0000
12       0.0302   0.0573   128.57  0.0000
13      -0.0602  -0.0105   139.39  0.0000
14      -0.0024   0.0197   139.41  0.0000
15       0.0122   0.0419   139.85  0.0000
16      -0.0008   0.0170   139.85  0.0000
17       0.0279   0.0332   142.18  0.0000
18       0.0188   0.0187   143.24  0.0000
19      -0.0260  -0.0305   145.25  0.0000
20       0.0335   0.0405    148.6  0.0000
```

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Chapter 8: Conclusion, Policy Recommendations and Future Research

This chapter summarises the discussions, findings, research contributions and policy recommendations in prior chapters.

Chapter 1 introduced the research. Banking crises repeatedly occur; for example, BCBS (2010) found at least one occurred every 20–25 years (with the exception of 1945 to the early 1970s/1980s). The economic cost of such crises is immense, with shocks spreading across a country, regional or the global economy through contagious effect. The 2008 global financial crises are an example of how crises triggered by systemic institutions can lead to widespread economic consequences. Our thesis focused on the banking sector, as it is the main player in many countries' financial systems. Therefore, it is crucial to safeguard against the possibility of SIBs failing and precipitating economic crises.

The importance of using the network model approach to study systemic risk as contagion emerged as the result of banks' daily operational activities and transactions. Banks and many financial institutions interact with other entities to manage liquidity and risks through interbank placement, bank funding and liabilities, which constructs a complex network within the financial sector. The implications of these activities are counterparty risk and systemic risk, which are realised when a bank failing to meet its obligations affects other banks or financial institutions in the system. The enormous efforts by scholars and policymakers to estimate the catastrophic effects of systemic failure are mostly based on market or publicly available data, and show little or no connection to that advised by the BCBS (2018) G-SIBs guideline. De Bandt and Hartmann (2000) and Bisias et al. (2012) show that researchers have not given much attention to analysis of macroeconomic factors that may be behind contagious default. Our study fills the theoretical gaps with an integrated model approach that uses micro or bank granular data and macroeconomic variables to identify SIBs and their systemic risk.

Chapter 2 reviewed prior studies of systemic risk. It began by showcasing the nonagreement between policymakers and researchers on the definition of systematic risk, and demonstrated that various indicators should be simultaneously considered to assess the complexity of systemic risk (Bengtsson, Holmberg & Jonsson 2013). The systemic risk literature can be classified into four major streams: probability distribution, contingent claims and default, network analysis and macroeconomics models. However, ECB (2009b) advised the importance of the two-sided interaction between individual financial institutions and the economy. Following the 2008 global financial crises, many countries constructed financial stress indexes consisting of various macroeconomic variables. The indexes in general were based on several economy blocks, like money market, debt and equity, securities and exchange rate. Policymakers also simulated scenarios to run stress tests for financial institutions to predict their soundness when crises hit. However, the indexes and stress tests had no or little connection to identifying SIBs, as they were standalone tools and tested separately. Chapter 2 also provided a summary of the Indonesian economy, justifying this thesis' use of Indonesian datasets to answer the research questions. Indonesia is a G20 country, one of the most important economies in Asia and features a large number of banks, yet it has received little scholarly attention regarding SIBs and banking systemic risk. Our study aimed to fill this identified gap in the literature.

Chapter 3 detailed the research methodology, data and models employed in our study. We categorised our study as mono method and quantitative in nature. Our research used secondary data, both global and country specific. The data sources consisted of market or publicly available data and banks' balance sheet data submitted to the regulator. Access to prudential data enabled our research to deliver valuable insights, as we could compare the results of market models with the Basel guideline results. Analysis in subsequent chapters used the theoretical market models of CoVaR by Adrian and Brunnermeier (2016); MES by Acharya, Engle and Richardson (2012); and SRISK by Brownlees and Engle (2017). BCBS (2018) is the benchmark guideline, whose results we compared the market models against. In formulating the interlinkages among financial entities and the network centrality, we applied PCA and Granger centrality (Billio et al. 2012). To integrate macro and micro data into SIB assessment, we used the ARCH (Engle 1982) and GARCH models (Bollerslev 1986).

Chapter 4 investigated how three widely cited theoretical market models could mimic the Basel prudential methodology used by regulators to shortlist D-SIBs. Using Indonesian banking data for the period 2008–2019, we used CoVaR, MES and SRISK to shortlist Indonesian D-SIBs, then compared the results with the prudential Basel D-SIBs list. The findings showed that each estimation model has distinctive advantages. In terms of D-SIB ranking stability, SRISK outperformed ΔCoVaR and MES. All three theoretical approaches have positive Kendall's association, but the highest match of the models' results with the Basel D-SIBs list is 47%. It seems that market data alone is insufficient to identify D-SIBs, and we suggest extending models to include published financial statement data to better capture banks' specific risk at the institution level. It would also be interesting to mix relevant country economy numbers into the equations and compare the results against the Basel guideline outcome.

Chapter 5 investigated how stock market data (share price, market capitalisation and asset returns) could be used to analyse interconnectedness within a financial system. Our datasets reflected Indonesian banks for the period 2012–2019, for which we employed PCA and Granger causality. We also used the Basel indicator-based approach to compare interconnectedness scores. The findings showed that returns co-movements exist in the Indonesian banking sector, which indicates interconnectedness. Eigenvalue plotting of the PCA method showed how the first three principal components could capture a significant portion of the variance. The outcome indicates the increase of risk commonality and interconnection in the financial system. The findings confirmed KBMI 4 and KBMI 3 banks to be the main contributors to interconnectedness. Granger causality results iterated the importance of intercorrelated exposure for SIB identification and tracing how risk might spread in the system. The degree Granger, closeness and eigenvector centrality showed KBMI 4 and KBMI 3 banks are the core banks in the Indonesian banking network, and their collapse would be catastrophic. Using the same centrality measures revealed that most KBMI 2 banks are in the network periphery. The outcome raised the issue of substitutability, given the dominance of large banks.

We compared the models' results with the Basel interconnectedness score that used prudential balance sheet data. The dominance of KBMI 4 and KBMI 3 banks was reconfirmed by the Basel indicator-based approach. The findings were consistent with those of Chapter 4 (Salim & Daly 2021). For future research, it is recommended to extend the estimation period to cover the 2007–2008 global financial crises and post-2019 to observe the effects of COVID-19 on systemic risk. It would be useful to use more balance sheet information and assess their overall connection to systematic risk. Finally, the findings suggested that a bank supervisor could monitor risk escalation and risk mapping using capital market and asset returns data. This outcome is also beneficial for policymakers to monitor interconnectedness among core banks that could trigger systemic risk.

Chapter 6 investigated market data as a proxy to map the interlinkages of the US financial system. We utilised US financial market statistics for the period 2002–2019 (Billio et al. 2012) to capture several crises, employing PCA and Granger causality. The findings showed that the pairwise returns correlation is significant at the 5% level and indicates pre-crisis interconnectedness and co-movement in the US financial market. In addition, the first three principal components captured a significant portion of returns variance. The outcome indicated an increase of interlinkages in the US financial system during crises. The findings also highlighted the importance of the banking sector in the US financial market.

Applying Granger causality, systemically important institutions were identified as banking and insurances entities. Centrality was proven as a good proxy to identify the central companies in a system. For future research, it is recommended to identify systemic financial institutions using extensive balance sheet data as compiled by a regulator. Further study of interconnectedness to explore balance sheet variables is appealing, as this will provide a clearer picture of risk. It would also be interesting to compare the results against other models using market data (e.g., CoVaR, MES and SRISK). Finally, the outcome indicated that for a regulator to validate and calibrate measures of systemically important institutions' risk exposure and effects on the country's economy requires multiple, complementary factors in the calculation.

Chapter 7 investigated how macroeconomic shocks could affect systemic risk through several transmission channels. To explore macroeconomic variables' connection to systemic risk, we employed three market models—CoVaR, MES and SRISK—using the adjusted linear equation from de Mendonça and Silva (2018) and expanding the analysis by employing fixed effects, random effects, ARCH and GARCH models. To consider the unobserved groups of variables that could affect the independent variables, we fit FMM. The findings showed that stock beta, market index volatility and exchange rate volatility amplify the transmission of systemic risk. The results were in line with our findings in Chapters 5 and 6 regarding the co-movement of asset returns. Change in anchor interest rate by a policymaker was proven to be significant, but the effect varies among the market models. The difference could stem from the models' employed variables and differences in interest rate time horizon. The effect of liquidity spread varies among the market models. Future research could explore the effects of certain model variables and financial market deepness on the outcome.

Finally, the chapter proposed practical improvement steps for the SIB assessment framework to better capture potential macroeconomic shocks. We also suggested technical integration and ratios that reflected the added steps. The integrated macro and micro granular data could portray overall risk endogenously and externally expose SIFIs.

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Appendices

Table A-1. CoVaR Results

Banks	Dec 08	%	Rank	Dec 09	%	Rank	Dec 10	%	Rank	Dec 11	%	Rank
BBCA	3.22898E-06	30.01%	2	1.67786E-06	25.38%	1	1.96343E-06	26.59%	1	1.28643E-06	21.71%	2
BBRI	1.69602E-06	15.76%	3	5.96477E-07	9.02%	4	7.15439E-07	9.69%	4	6.00341E-07	10.13%	5
BMRI	3.32822E-06	30.94%	1	1.12467E-06	17.01%	2	1.45135E-06	19.66%	2	1.32974E-06	22.44%	1
BBNI	6.51383E-07	6.05%	4	6.06282E-07	9.17%	3	6.3008E-07	8.53%	5	6.04106E-07	10.20%	4
MEGA	1.16317E-07	1.08%		5.27341E-07	7.98%	5	1.34848E-07	1.83%		1.16316E-07	1.96%	
MAYA	6.31115E-09	0.06%		1.78698E-08	0.27%		2.00223E-08	0.27%		5.59844E-09	0.09%	
BNLI	-2.07074E-10	0.00%		-2.07074E-10	0.00%		-2.07074E-10	0.00%		-2.07074E-10	0.00%	
BDMN	1.63744E-07	1.52%		1.06261E-07	1.61%		1.4508E-07	1.97%		9.89851E-08	1.67%	
PNBN	1.00803E-07	0.94%		7.95583E-08	1.20%		7.74842E-08	1.05%		8.66466E-08	1.46%	
NISP	4.82001E-08	0.45%		5.73479E-08	0.87%		5.76422E-09	0.08%		5.297E-09	0.09%	
BNGA	1.11736E-09	0.01%		1.11736E-09	0.02%		1.11736E-09	0.02%		1.11736E-09	0.02%	
BTPN	5.11789E-08	0.48%		5.22887E-08	0.79%		5.12569E-08	0.69%		5.19103E-08	0.88%	
BNII	2.07002E-08	0.19%		2.14318E-08	0.32%		1.95067E-08	0.26%		2.09395E-08	0.35%	
BJBR	3.75353E-07	3.49%		3.75353E-07	5.68%	6	7.76017E-07	10.51%	3	6.11985E-07	10.33%	3
BTN	5.0581E-09	0.05%		7.69058E-08	1.16%		2.25135E-07	3.05%		1.28588E-07	2.17%	
BSIM	4.13653E-08	0.38%		4.13653E-08	0.63%		3.70522E-07	5.02%	6	1.89964E-07	3.21%	
BJTM	9.87112E-09	0.09%		9.87112E-09	0.15%		9.87112E-09	0.13%		9.87112E-09	0.17%	
SDRA	1.52004E-07	1.41%		1.88677E-07	2.85%		1.5173E-07	2.06%		1.71067E-07	2.89%	
BACA	2.25551E-07	2.10%		2.39373E-07	3.62%		2.61144E-07	3.54%		2.45228E-07	4.14%	
AGRO	2.54908E-08	0.24%		7.51543E-08	1.14%		3.47568E-08	0.47%		3.02167E-08	0.51%	
CCBI	1.6168E-07	1.50%		2.93905E-07	4.45%		5.3942E-08	0.73%		2.14091E-08	0.36%	
BBKP	1.8223E-07	1.69%		1.44039E-07	2.18%		1.58147E-07	2.14%		1.91311E-07	3.23%	
BABP	1.32019E-07	1.23%		2.82504E-07	4.27%		1.26153E-07	1.71%		1.26274E-07	2.13%	
BKSW	6.48735E-08	0.60%		5.74457E-08	0.87%		1.89854E-08	0.26%		1.52997E-08	0.26%	
INPC	-2.0919E-09	-0.02%		-1.54992E-08	-0.23%		-5.42136E-09	-0.07%		-8.83613E-09	-0.15%	
BNBA	-1.86965E-08	-0.17%		-1.30546E-08	-0.20%		-6.71165E-09	-0.09%		-9.12981E-09	-0.15%	
BVIC	-8.87694E-09	-0.08%		-1.40752E-08	-0.21%		-6.5006E-09	-0.09%		-5.69528E-09	-0.10%	
	1.07586E-05			**6.61027E-06**			**7.38294E-06**			**5.92477E-06**		

Banks	Dec 12	%	Rank	Dec 13	%	Rank	Dec 14	% t	Rank	Dec 15	%	Rank
BBCA	2.28144E-06	30.92%	1	1.74342E-06	25.14%	1	1.00641E-06	19.01%	2	1.74148E-06	24.69%	1
BBRI	4.75032E-07	6.44%	6	7.44284E-07	10.73%	3	5.25771E-07	9.93%	4	7.95881E-07	11.28%	3
BMRI	1.24669E-06	16.90%	2	1.559E-06	22.48%	2	1.02461E-06	19.35%	1	1.47219E-06	20.87%	2
BBNI	6.01215E-07	8.15%	4	6.01313E-07	8.67%	4	6.04716E-07	11.42%	3	6.05522E-07	8.58%	5
MEGA	1.52582E-07	2.07%		1.16848E-07	1.68%		1.16455E-07	2.20%		1.16334E-07	1.65%	
MAYA	1.58472E-08	0.21%		1.73729E-08	0.25%		7.78801E-09	0.15%		6.61141E-09	0.09%	
BNLI	-1.51462E-08	-0.21%		-1.20766E-08	-0.17%		-1.31781E-08	-0.25%		-3.24094E-08	-0.46%	
BDMN	1.06717E-07	1.45%		1.42722E-07	2.06%		1.03919E-07	1.96%		1.33932E-07	1.90%	
PNBN	8.0878E-08	1.10%		7.95254E-08	1.15%		7.65758E-08	1.45%		7.57504E-08	1.07%	
NISP	5.68694E-09	0.08%		4.26634E-09	0.06%		4.35877E-09	0.08%		3.50161E-09	0.05%	
BNGA	2.17098E-08	0.29%		2.40825E-08	0.35%		2.28384E-08	0.43%		2.76512E-08	0.39%	
BTPN	5.15499E-08	0.70%		5.12894E-08	0.74%		5.12122E-08	0.97%		5.23213E-08	0.74%	
BNII	1.98488E-08	0.27%		1.9724E-08	0.28%		1.85278E-08	0.35%		2.37857E-08	0.34%	
BJBR	8.42161E-07	11.41%	3	5.08119E-07	7.33%	5	5.14944E-07	9.73%	5	6.30386E-07	8.94%	4
BTN	1.68631E-07	2.29%		2.14839E-07	3.10%		1.52789E-07	2.89%		9.96335E-08	1.41%	
BSIM	9.18147E-08	1.24%		5.42655E-08	0.78%		8.13291E-08	1.54%		1.00519E-07	1.43%	
BJTM	5.20997E-07	7.06%	5	4.32117E-07	6.23%	6	4.18081E-07	7.90%	6	4.42947E-07	6.28%	6
SDRA	1.7823E-07	2.42%		1.5723E-07	2.27%		1.50483E-07	2.84%		1.58348E-07	2.24%	
BACA	1.90307E-07	2.58%		1.71333E-07	2.47%		1.80059E-07	3.40%		2.27694E-07	3.23%	
AGRO	3.58569E-08	0.49%		3.84557E-08	0.55%		3.77241E-08	0.71%		3.35053E-08	0.48%	
CCBI	2.33243E-08	0.32%		5.02458E-08	0.72%		2.20969E-08	0.42%		1.28463E-07	1.82%	
BBKP	1.51057E-07	2.05%		1.49927E-07	2.16%		1.19467E-07	2.26%		1.26066E-07	1.79%	
BABP	1.3322E-07	1.81%		6.76E-08	0.97%		6.64191E-08	1.25%		8.23887E-08	1.17%	
BKSW	1.43355E-08	0.19%		1.62908E-08	0.23%		1.59569E-08	0.30%		2.35055E-08	0.33%	
INPC	-2.4593E-09	-0.03%		-3.00951E-09	-0.04%		-3.00857E-09	-0.06%		-3.8511E-09	-0.05%	
BNBA	-8.54855E-09	-0.12%		-9.09803E-09	-0.13%		-7.42502E-09	-0.14%		-8.40966E-09	-0.12%	
BVIC	-4.31901E-09	-0.06%		-5.2143E-09	-0.08%		-4.71887E-09	-0.09%		-1.0015E-08	-0.14%	
	7.37865E-06			**6.93487E-06**			**5.2942E-06**			**7.05373E-06**		
	Dec 12	**%**	**Rank**	**Dec 13**	**%**	**Rank**						

Dec 16	%	Rank	Dec 17	%	Rank	Dec 18	%	Rank	Dec 19	%	Rank
1.34859E-06	14.90%	3	1.15045E-06	20.09%	1	1.21812E-06	20.55%	1	1.23617E-06	19.75%	1
6.35581E-07	7.02%	5	5.3091E-07	9.27%	5	4.68093E-07	7.90%	5	4.70972E-07	7.52%	5
1.26992E-06	14.03%	4	9.68993E-07	16.92%	2	1.11873E-06	18.88%	2	9.51125E-07	15.20%	3
6.10623E-07	6.75%	6	6.01536E-07	10.50%	3	6.01999E-07	10.16%	4	6.0222E-07	9.62%	4
1.21089E-07	1.34%		1.84814E-07	3.23%		1.42405E-07	2.40%		1.18514E-07	1.89%	
5.67936E-09	0.06%		6.24874E-09	0.11%		5.60333E-09	0.09%		5.65953E-09	0.09%	
-1.40991E-08	-0.16%		-8.42399E-09	-0.15%		-2.97968E-08	-0.50%		-2.38172E-08	-0.38%	
1.21153E-07	1.34%		2.13442E-07	3.73%		1.05606E-07	1.78%		1.13819E-07	1.82%	
7.74701E-08	0.86%		7.52806E-08	1.31%		9.57981E-08	1.62%		8.74281E-08	1.40%	
9.5213E-09	0.11%		3.82223E-09	0.07%		3.37058E-09	0.06%		3.38431E-09	0.05%	
3.59121E-08	0.40%		3.51942E-08	0.61%		3.82197E-08	0.64%		2.55073E-08	0.41%	
5.14642E-08	0.57%		5.22179E-08	0.91%		5.1596E-08	0.87%		5.20021E-08	0.83%	
2.38046E-08	0.26%		1.59904E-08	0.28%		1.65949E-08	0.28%		1.81373E-08	0.29%	
2.1283E-06	23.52%	1	5.37129E-07	9.38%	4	7.05955E-07	11.91%	3	1.06029E-06	16.94%	2
2.39588E-07	2.65%		1.23685E-07	2.16%		1.87945E-07	3.17%		1.55899E-07	2.49%	
7.28369E-08	0.80%		2.86155E-07	5.00%		1.45239E-07	2.45%		1.62374E-07	2.59%	
1.5579E-06	17.21%	2	3.74838E-07	6.54%	6	4.17298E-07	7.04%	6	3.73706E-07	5.97%	6
1.50474E-07	1.66%		1.50625E-07	2.63%		1.95026E-07	3.29%		3.58291E-07	5.72%	7
1.73138E-07	1.91%		1.59005E-07	2.78%		1.99792E-07	3.37%		1.56752E-07	2.50%	
8.39974E-08	0.93%		2.81023E-08	0.49%		2.76711E-08	0.47%		7.50154E-08	1.20%	
2.65067E-08	0.29%		2.08199E-08	0.36%		2.07215E-08	0.35%		2.0455E-08	0.33%	
2.07216E-07	2.29%		1.50698E-07	2.63%		1.48724E-07	2.51%		1.69278E-07	2.70%	
9.92199E-08	1.10%		5.78664E-08	1.01%		4.58202E-08	0.77%		4.811E-08	0.77%	
3.83797E-08	0.42%		2.56881E-08	0.45%		1.60789E-08	0.27%		4.84638E-08	0.77%	
-6.6545E-09	-0.07%		-3.14536E-09	-0.05%		-2.65354E-09	-0.04%		-2.78869E-09	-0.04%	
-9.19721E-09	-0.10%		-5.94023E-09	-0.10%		-5.78694E-09	-0.10%		-5.06236E-09	-0.08%	
-8.13168E-09	-0.09%		-8.50371E-09	-0.15%		-1.12326E-08	-0.19%		-2.25791E-08	-0.36%	
9.05029E-06			**5.7275E-06**			**5.92694E-06**			**6.25933E-06**		

Table A-2. Marginal Expected Shortfall (MES) Results

Banks	Dec 08	% to sys	Rank	Dec 09	% to sys	Rank	Dec 10	% to sys	Rank	Dec 11	% to sys	Rank	Dec 12	% to sys	Rank	Dec 13	% to sys	Rank
BBCA	0.055370	10.77	3	0.0260899	8.00	4	0.02793	7.12%	5	0.022421	5.29	8	0.03078	9.79%	1	0.028681	6.77	6
BBRI	0.084868	16.51	1	0.0227840	6.99	6	0.03139	8.00%	2	0.027644	6.52	6	0.01767	5.62%	7	0.035808	8.45	2
BMRI	0.079929	15.55	2	0.0244607	7.50	5	0.03269	8.33%	1	0.029929	7.06	5	0.02441	7.76%	3	0.032835	7.75	3
BBNI	0.050754	9.88	4	0.0424459	13.02	1	0.02704	6.89%	6	0.043140	10.18	1	0.00376	1.20%		0.044505	10.51	1
MEGA	0.005177	1.01		-	-		0.00728	1.86%		0.005491	1.30		0.00627	1.99%		0.005947	1.40	
MAYA	0.002226	0.43		-	-		0.01683	4.29%		0.001155	0.27		0.00588	1.87%		0.007936	1.87	
BNLI	5.22667E	0.01		5.05353E-	0.02		5.26627	0.01%		5.54979E	0.01		0.00450	1.43%		0.004546	1.07	
BDMN	0.034301	6.67	6	0.0220642	6.77	7	0.03039	7.75%	3	0.019340	4.56		0.02045	6.50%	5	0.029333	6.93	4
PNBN	0.043019	8.37	5	0.0215188	6.60	9	0.02646	6.74%	7	0.033940	8.01	2	0.03062	9.74%	2	0.029253	6.91	5
NISP	0.008070	1.57		0.0096027	2.95		0.00096	0.25%		0.000891	0.21		0.00095	0.30%		0.000719	0.17	
BNGA	5.58608E	0.01		7.4549E-	0.02		9.08012	0.02%		7.62407E	0.02		0.00478	1.52%		0.011940	2.82	
BTPN	0.006171	1.20		0.0166189	5.10	11	0.01297	3.31%		0.024441	5.77	7	0.01274	4.05%		0.017904	4.23	
BNII	0.007093	1.38		0.0163150	5.01	12	0.01415	3.61%		0.017632	4.16		0.01051	3.34%		0.010835	2.56	
BJBR	0.003270	0.64		0.0031052	0.95		0.02517	6.42%	8	0.021155	4.99		0.01825	5.80%	6	0.013299	3.14	
BTN	0.000484	0.09		0.0095066	2.92		0.02993	7.63%	4	0.019700	4.65		0.01344	4.28%		0.024426	5.77	7
BSIM	0.000980	0.19		0.0008987	0.28		-	-		0.032334	7.63	3	0.00807	2.57%		0.003014	0.71	
BJTM	0.000182	0.04		0.0001500	0.05		0.00012	0.03%		0.000166	0.04		0.01032	3.28%		0.012502	2.95	
SDRA	0.022690	4.41		0.0189380	5.81	10	0.01788	4.56%		0.022371	5.28	9	0.01196	3.80%		0.016484	3.89	
BACA	0.009556	1.86		0.0005926	0.18		0.00147	0.38%		0.005410	1.28		2.43733	0.01%		0.006613	1.56	
AGRO	0.014563	2.83		0.0221336	6.79	7	0.01339	3.41%		0.010200	2.41		0.01234	3.92%		0.009253	2.18	
CCBI	-	-		-	-		0.01530	3.90%		0.006812	1.61		0.00628	2.00%		0.005705	1.35	
BBKP	0.029112	5.66	7	0.0220580	6.77	8	0.02088	5.32%	9	0.030391	7.17	4	0.02202	7.00%	4	0.022094	5.22	8
BABP	0.012534	2.44		0.0301230	9.24	2	0.00468	1.19%		0.000279	0.07		0.01085	3.45%		0.016016	3.78	
BKSW	0.005036	0.98		0.0037406	1.15		0.00133	0.34%		0.000992	0.23		0.00093	0.30%		0.001140	0.27	
INPC	0.005060	0.98		0.0162289	4.98		0.01409	3.59%		0.021860	5.16	10	0.00559	1.78%		0.008789	2.08	
BNBA	0.020233	3.94		0.0112986	3.47		0.00827	2.11%		0.009638	2.27		0.00708	2.25%		0.007001	1.65	
BVIC	0.017820	3.47		0.0285211	8.75	3	0.01327	3.38%		0.016470	3.88		0.01399	4.45%		0.016959	4.00	
	0.513945			**0.3259285**			**0.39237**			**0.423948**			**0.31458**			**0.423550**		

Banks	Dec 14	% to sys	Rank	Dec 15	% to sys	Rank	Dec 16	% to sys	Rank	Dec 17	% to sys	Rank	Dec 18	% to sys	Rank	Dec 19	% to sys	Rank
BBCA	0.016907	5.27	7	0.0304606	7.49	4	0.02100	4.07%		0.017452	6.27	4	0.01560	4.45%		0.018736	5.21	9
BBRI	0.025372	7.90	2	0.0401875	9.89	2	0.03101	6.01%	6	0.022651	8.14	3	0.02227	6.36%	6	0.020744	5.77	7
BMRI	0.022541	7.02	3	0.0354394	8.72	3	0.02881	5.58%	8	0.016233	5.83	6	0.02568	7.33%	3	0.019786	5.50	8
BBNI	0.038833	12.10	1	0.0439157	10.80	1	0.04300	8.33%	1	0.034030	12.23	2	0.03929	11.22	1	0.037244	10.36	2
MEGA	0.006181	1.93		0.0056680	1.39		0.00248	0.48%		0.017150	6.16	5	0.01075	3.07%		0.007348	2.04	
MAYA	0.001867	0.58		0.0018635	0.46		0.00101	0.20%		0.001353	0.49		0.00124	0.36%		0.001298	0.36	
BNLI	0.003793	1.18		0.0103554	2.55		0.00606	1.18%		0.001430	0.51		0.00665	1.90%		0.007225	2.01	
BDMN	0.021661	6.75	4	0.0272008	6.69	5	0.03112	6.03%	5	0.047541	17.08	1	0.02391	6.83%	5	0.021750	6.05	5
PNBN	0.020996	6.54	5	0.0208951	5.14	8	0.02548	4.94%		0.005047	1.81		0.02099	5.99%	7	0.024751	6.88	4
NISP	0.000734	0.23		0.0005912	0.15		0.00159	0.31%		0.000644	0.23		0.00056	0.16%		0.000571	0.16	
BNGA	0.008193	2.55		0.0067957	1.67		0.01648	3.20%		0.006291	2.26		0.01292	3.69%		0.014203	3.95	
BTPN	0.012332	3.84		0.0107106	2.63		0.01018	1.97%		0.011008	3.96		0.01294	3.70%		0.014051	3.91	
BNII	0.007872	2.45		0.0102557	2.52		0.01489	2.89%		0.006518	2.34		0.00698	1.99%		0.009804	2.73	
BJBR	0.015007	4.68		0.0193264	4.75		0.02629	5.10%	9	-	-		0.00913	2.61%		-	-	
BTN	0.020641	6.43	6	0.0125824	3.10		0.03751	7.27%	3	0.008468	3.04		0.02828	8.08%	2	0.018734	5.21	10
BSIM	0.001763	0.55		0.0026080	0.64		0.00132	0.26%		0.005347	1.92		0.01051	3.00%		-	-	
BJTM	0.008253	2.57		0.0129691	3.19		0.03615	7.01%	4	0.002038	0.73		0.00670	1.91%		0.006426	1.79	
SDRA	0.013231	4.12		0.0107658	2.65		0.01049	2.03%		0.007752	2.79		0.00689	1.97%		0.014104	3.92	
BACA	0.005195	1.62		0.0210645	5.18	7	0.02126	4.12%		0.006620	2.38		0.00893	2.55%		0.007817	2.17	
AGRO	0.010442	3.25		0.0128322	3.16		0.04094	7.94%	2	0.010704	3.85		0.01211	3.46%		0.031945	8.88	3
CCBI	0.008226	2.56		-	-		0.01153	2.23%		0.007580	2.72		0.00614	1.75%		0.005768	1.60	
BBKP	0.015930	4.96		0.0167994	4.13		0.02982	5.78%	7	0.014070	5.06	7	0.02084	5.95%	8	0.020942	5.82	6
BABP	0.011959	3.73		0.0229763	5.65	6	0.02142	4.15%		0.007085	2.55		0.00459	1.31%		0.004838	1.35	
BKSW	0.001041	0.32		0.0015135	0.37		0.00247	0.48%		0.001702	0.61		0.00102	0.29%		0.003156	0.88	
INPC	0.008699	2.71		0.0096292	2.37		0.01741	3.37%		0.006002	2.16		0.00506	1.44%		0.006820	1.90	
BNBA	0.006588	2.05		0.0060583	1.49		0.01107	2.15%		0.004495	1.62		0.00579	1.65%		0.004598	1.28	
BVIC	0.006727	2.10		0.0164369	4.04		0.01507	2.92%		0.010816	3.89		0.02436	6.96%	4	0.045850	12.75	1
	0.320996			**0.4065045**			**0.51599**			**0.278332**			**0.35026**			**0.359557**		

Table A-3. SRISK Results

Banks	Dec 08	% to sys	Rank	Dec 09	% to sys	Rank	Dec 10	% to sys	Rank	Dec 11	% to sys	Rank	Dec 12	% to sys	Rank	Dec 13	% to sys	Rank
BBCA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BBRI	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BMRI	9,505,267.	31.14	1	-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BBNI	8,902,782.	29.17	2	2,768,184.	16.13	3	-	0.00		1,780,862.	7.43	3	-	0.00%		6,252,441.	39.87	1
MEGA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
MAYA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BNLI	3,448,410.	11.30	4	4,160,491.	24.24	2	4,893,4	31.85	2	6,697,222.	27.93	2	-	0.00%		-	0.00%	
BDMN	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
PNBN	-	0.00		-	0.00%		-	0.00		592,996.2	2.47		5,106,835.9	70.17	1	3,453,632.	22.02	3
NISP	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BNGA	7,511,608.	24.61	3	7,671,509.	44.70	1	10,390,	67.64	1	11,879,88	49.54	1	-	0.00%		-	0.00%	
BTPN	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BNII	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BJBR	-	0.00		2,345,502.	13.67	4	-	0.00		-	0.00		278,630.99	3.83%		-	0.00%	
BTN	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		4,190,124.	26.72	2
BSIM	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BJTM	-	0.00		-	0.00%		-	0.00		1,378,459.	5.75	4	-	0.00%		-	0.00%	
SDRA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BACA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
AGRO	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
CCBI	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BBKP	856,876.9	2.81		-	0.00%		-	0.00		968,510.2	4.04		1,345,239.5	18.48	2	713,635.7	4.55%	
BABP	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BKSW	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
INPC	269,303.3	0.88		216,616.8	1.26%		77,993.	0.51		587,728.5	2.45		141,787.09	1.95%		400,921.8	2.56%	
BNBA	26,402.69	0.09		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BVIC	-	0.00		-	0.00%		-	0.00		93,537.11	0.39		405,205.64	5.57%	3	672,949.5	4.29%	
	30,520,65			**17,162,30**			**15,362,**			**23,979,19**			**7,277,699.2**			**15,683,70**		

Banks	Dec 14	% to sys	Rank	Dec 15	% to sys	Rank	Dec 16	% to sys	Rank	Dec 17	% to sys	Rank	Dec 18	% to sys	Rank	Dec 19	% to sys	Rank
BBCA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BBRI	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BMRI	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BBNI	-	0.00		4,582,931.	23.91	2	7,020,6	26.65	2	1,574,113.	26.11	2	15,830,863.	40.78	1	26,507,01	49.14	1
MEGA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
MAYA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BNLI	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BDMN	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
PNBN	-	0.00		-	0.00%		2,608,7	9.90		-	0.00		-	0.00%		-	0.00%	
NISP	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BNGA	1,613,450.	19.62	2	5,164,151.	26.94	1	3,363,8	12.77	4	-	0.00		4,445,588.0	11.45	4	5,675,101.	10.52	4
BTPN	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		1,060,008.	1.97%	
BNII	-	0.00		1,441,790.	7.52%	5	-	0.00		-	0.00		100,530.78	0.26%		774,254.2	1.44%	
BJBR	1,329,286.	16.16	3	2,065,232.	10.77	4	-	0.00		-	0.00		-	0.00%		-	0.00%	
BTN	3,558,571.	43.27	1	2,584,133.	13.48	3	7,401,3	28.09	1	-	0.00		11,085,529.	28.55	2	10,870,51	20.15	2
BSIM	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BJTM	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
SDRA	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BACA	66,546.65	0.81		-	0.00%		153,395	0.58		-	0.00		-	0.00%		-	0.00%	
AGRO	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		377,148.5	0.70%	
CCBI	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BBKP	151,708.8	1.84		1,268,472.	6.62%	6	3,519,5	13.36	3	3,180,791.	52.75	1	5,186,285.7	13.36	3	5,900,988.	10.94	3
BABP	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
BKSW	-	0.00		-	0.00%		-	0.00		-	0.00		-	0.00%		-	0.00%	
INPC	755,073.4	9.18	4	1,016,808.	5.30%	7	1,004,0	3.81		874,671.6	14.51	3	923,501.83	2.38%		966,176.8	1.79%	
BNBA	76,673.41	0.93		60,410.69	0.32%		121,168	0.46		-	0.00		-	0.00%		-	0.00%	
BVIC	673,549.8	8.19	5	983,091.6	5.13%	8	1,151,2	4.37		400,008.3	6.63	4	1,250,760.9	3.22%		1,807,549.	3.35%	
	8,224,860.			**19,167,02**			**26,344,**			**6,029,585.**			**38,823,061.**			**53,938,76**		

Table A-4. Basel Indicator-Based Results

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	*Interbank assets*	*Interbank liabilities*	*Securities Outstand.*	*OTC Derivatives*	*Trading & AFS*	*Country Specific Indicator*	*Substitutability*	Size	Interconnectedness	Complexity	
		100.00%	**33.33%**	**33.33%**	**33.33%**	**25.00%**	**25.00%**	**25.00%**	**25.00%**	**33.33%**	**33.33%**	**33.33%**	
	Jun-15												
13	Bank 2	1331	1092	1908	1945	1185	1691	1071	1038	1331	1648	1246	1408
7	Bank 1	1180	603	814	2118	12	675	1660	1419	1180	1178	941	1100
19	Bank 6	974	650	94	2761	336	997	698	888	974	1168	730	957
14	Bank 3	647	674	380	820	0	555	638	493	647	625	421	564
27	Bank 9	406	274	218	172	545	794	284	376	406	221	500	376
16	Bank 4	288	306	236	348	67	500	578	221	288	297	342	309
46	Bank 18	278	132	360	0	833	223	185	600	278	164	460	301
55	Bank 24	182	315	197	0	1493	24	124	495	182	171	534	296
47	Bank 19	273	547	93	0	1308	25	69	75	273	213	369	285
18	Bank 5	333	113	417	158	85	210	541	192	333	229	257	273
72	Bank 29	66	108	105	0	576	31	154	1646	66	71	602	246
24	Bank 8	259	546	252	231	8	244	134	118	259	343	126	243
33	Bank 11	214	195	199	148	331	528	161	90	214	180	278	224
36	Bank 12	186	144	95	0	451	86	485	587	186	80	402	223
205	Bank 73	229	164	447	171	0	283	182	62	229	261	132	207
21	Bank 7	231	170	188	125	177	215	207	149	231	161	187	193
431	Bank 79	115	74	116	144	51	826	164	110	115	112	288	171
115	Bank 37	128	349	348	66	0	49	107	62	128	254	54	146
51	Bank 21	147	40	168	0	411	150	74	90	147	69	181	132
446	Bank 81	125	113	349	50	32	162	119	51	125	171	91	129
28	Bank 10	146	33	92	11	83	160	184	165	146	45	148	113
50	Bank 20	119	187	202	7	316	0	2	29	119	132	87	113
37	Bank 13	38	135	48	0	742	0	60	36	38	61	210	103
218	Bank 75	106	87	206	166	0	79	80	37	106	153	49	103
66	Bank 28	92	123	27	0	253	61	65	29	92	50	102	81
53	Bank 23	95	109	40	0	176	140	28	35	95	50	95	80
456	Bank 82	91	85	33	2	0	70	168	55	91	40	74	68
152	Bank 65	78	32	170	12	0	70	91	30	78	71	48	66
119	Bank 41	77	196	17	59	0	0	76	23	77	91	25	64
62	Bank 27	25	77	110	0	257	60	9	14	25	62	85	57

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	***Interbank assets***	***Interbank liabilities***	***Securities Outstand.***	***OTC Derivatives***	***Trading & AFS***	***Country Specific Indicator***	***Substituta bility***	**Size**	**Interconnected ness**	**Complexity**	
		100.00%	**33.33%**	**33.33%**	**33.33%**	**25.00%**	**25.00%**	**25.00%**	**25.00%**	**33.33%**	**33.33%**	**33.33%**	
	Dec-15												
13	Bank 2	1312	1339	1344	1874	783	1976	774	1000	1312	1519	1133	1321
7	Bank 1	1295	498	1229	2448	274	365	1920	550	1295	1392	777	1155
19	Bank 6	960	453	87	2848	373	940	683	1166	960	1129	791	960
14	Bank 3	741	837	430	808	333	812	695	471	741	692	578	670
27	Bank 9	385	334	279	136	582	935	297	435	385	250	562	399
47	Bank 19	281	715	107	0	1531	0	61	108	281	274	425	327
55	Bank 24	170	342	241	0	1258	0	128	504	170	194	473	279
16	Bank 4	258	268	206	266	67	498	432	275	258	247	318	274
24	Bank 8	260	674	196	178	6	472	141	157	260	350	194	268
46	Bank 18	230	97	379	0	782	6	150	527	230	159	366	252
431	Bank 79	117	228	107	198	26	1552	142	105	117	178	456	251
18	Bank 5	310	163	301	98	180	0	465	235	310	187	220	239
72	Bank 29	66	80	81	0	398	13	125	1579	66	54	529	216
36	Bank 12	180	249	88	0	366	0	369	602	180	112	334	209
33	Bank 11	210	100	163	146	246	270	430	121	210	136	267	205
21	Bank 7	239	191	206	107	200	214	191	177	239	168	195	201
205	Bank 73	243	90	571	119	0	40	181	99	243	260	80	194
115	Bank 37	116	199	460	64	6	106	117	78	116	241	77	144
51	Bank 21	136	52	210	0	394	138	79	104	136	87	179	134
50	Bank 20	137	220	189	7	309	0	21	48	137	139	95	123
28	Bank 10	148	29	103	5	85	27	229	203	148	46	136	110
37	Bank 13	35	136	64	0	722	0	72	57	35	67	213	105
446	Bank 81	132	174	106	55	0	15	131	67	132	112	53	99
66	Bank 28	95	110	71	0	410	12	77	40	95	60	134	97
218	Bank 75	104	55	239	122	0	25	85	44	104	139	39	94
456	Bank 82	93	92	38	1	0	149	186	60	93	43	99	78
152	Bank 65	78	56	157	2	0	135	104	35	78	71	68	73
53	Bank 23	104	133	21	0	169	0	26	52	104	51	61	72
571	Bank 113	31	123	70	8	0	393	11	13	31	67	104	67
169	Bank 71	78	78	107	0	9	46	69	12	78	62	34	58
13	Bank 2	1326	867	1100	1895	651	2018	744	1033	1326	1287	1112	1242
7	Bank 1	1283	441	1296	2272	440	606	1875	502	1283	1336	856	1158
19	Bank 6	992	604	111	2801	481	1429	751	1165	992	1172	956	1040
14	Bank 3	752	775	515	830	435	751	800	502	752	707	622	694

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	*Interbank assets*	*Interbank liabilities*	*Securities Outstand.*	*OTC Derivatives*	*Trading & AFS*	*Country Specific Indicator*	*Substituta bility*	Size	Interconnected ness	Complexity	
		100.00%	33.33%	33.33%	33.33%	25.00%	25.00%	25.00%	25.00%	33.33%	33.33%	33.33%	
27	Bank 9	378	346	227	119	564	813	308	427	378	231	528	379
47	Bank 19	282	728	101	0	1373	0	74	117	282	276	391	316
55	Bank 24	152	371	263	0	1269	0	108	516	152	211	473	279
16	Bank 4	237	276	213	289	58	540	440	272	237	259	327	275
24	Bank 8	265	777	193	174	40	380	135	154	265	381	177	274
18	Bank 5	293	192	339	135	167	0	422	251	293	222	210	242
21	Bank 7	240	222	212	164	224	355	198	180	240	199	239	226
205	Bank 73	258	104	700	155	0	83	176	114	258	320	93	224
72	Bank 29	62	133	119	0	327	0	159	1577	62	84	516	221
46	Bank 18	239	80	80	0	709	5	166	534	239	53	354	215
33	Bank 11	215	118	202	136	258	261	418	115	215	152	263	210
36	Bank 12	168	204	86	0	330	0	334	595	168	97	315	193
431	Bank 79	109	203	169	211	43	733	135	104	109	194	254	186
51	Bank 21	135	36	236	0	400	207	95	100	135	90	200	142
115	Bank 37	123	214	403	93	1	91	110	57	123	237	65	142
50	Bank 20	137	229	239	6	278	0	7	55	137	158	85	127
28	Bank 10	146	42	82	4	105	26	233	187	146	43	138	109
37	Bank 13	32	182	36	0	760	0	49	54	32	73	216	107
446	Bank 81	132	97	141	44	13	158	120	78	132	94	92	106
218	Bank 75	108	39	270	123	36	24	95	42	108	144	49	100
66	Bank 28	77	103	37	0	364	9	72	43	77	46	122	82
53	Bank 23	99	165	55	0	173	0	30	56	99	74	65	79
456	Bank 82	92	101	33	0	0	134	176	46	92	45	89	75
152	Bank 65	68	48	203	0	0	0	87	31	68	83	30	60
571	Bank 113	32	122	70	9	0	306	11	13	32	67	82	60
169	Bank 71	70	85	98	0	32	52	78	16	70	61	45	59
	Dec-16												
13	Bank 2	1353	964	921	1939	821	1770	812	1068	1353	1274	1118	1248
7	Bank 1	1327	453	930	2274	340	543	1725	591	1327	1219	800	1115
19	Bank 6	1000	652	117	2795	304	2004	800	1154	1000	1188	1066	1084
14	Bank 3	811	855	622	782	599	822	797	528	811	753	687	750
27	Bank 9	365	277	222	153	537	638	296	454	365	217	481	355
47	Bank 19	270	827	67	0	1505	0	97	121	270	298	431	333
16	Bank 4	229	389	185	284	46	405	426	264	229	286	285	267
55	Bank 24	152	332	251	0	1134	0	106	505	152	194	436	261

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	*Interbank assets*	*Interbank liabilities*	*Securities Outstand.*	*OTC Derivatives*	*Trading & AFS*	*Country Specific Indicator*	*Substitutability*	Size	Interconnectedness	Complexity	
		100.00%	**33.33%**	**33.33%**	**33.33%**	**25.00%**	**25.00%**	**25.00%**	**25.00%**	**33.33%**	**33.33%**	**33.33%**	
24	Bank 8	266	704	88	166	43	311	152	149	266	319	164	250
205	Bank 73	277	101	696	175	0	125	186	122	277	324	108	236
21	Bank 7	233	238	207	158	178	457	200	178	233	201	253	229
33	Bank 11	226	129	199	155	181	254	467	113	226	161	254	214
36	Bank 12	167	174	100	0	503	0	317	633	167	91	363	207
46	Bank 18	205	55	75	0	500	5	126	811	205	43	360	203
18	Bank 5	246	176	237	97	95	0	385	255	246	170	184	200
72	Bank 29	57	97	68	0	357	0	139	1272	57	55	442	185
431	Bank 79	109	340	130	167	43	661	137	97	109	212	235	185
115	Bank 37	124	203	616	110	12	44	105	53	124	310	54	162
50	Bank 20	161	274	343	6	291	0	8	51	161	208	88	152
446	Bank 81	134	166	406	46	14	196	125	74	134	206	103	147
51	Bank 21	133	51	153	0	405	200	136	111	133	68	213	138
28	Bank 10	149	48	76	9	173	22	234	70	149	44	125	106
37	Bank 13	31	172	32	0	714	0	37	48	31	68	200	100
218	Bank 75	106	48	267	123	10	11	109	32	106	146	40	97
66	Bank 28	71	76	48	0	371	8	60	39	71	42	119	77
53	Bank 23	96	160	45	0	172	0	29	53	96	68	63	76
456	Bank 82	95	87	40	0	0	106	190	53	95	42	87	75
118	Bank 40	63	77	165	0	0	74	73	29	63	81	44	63
62	Bank 27	32	96	109	0	314	0	16	18	32	68	87	62
169	Bank 71	73	76	108	0	21	46	65	17	73	61	37	57
	Jun-17												
13	Bank 2	1327	962	888	1864	986	1508	842	1091	1327	1238	1107	1224
7	Bank 1	1298	450	1156	2256	320	602	1736	513	1298	1287	793	1126
19	Bank 6	1055	666	230	2680	344	1969	840	1113	1055	1192	1066	1105
14	Bank 3	792	647	635	767	757	739	803	603	792	683	725	733
27	Bank 9	355	262	194	204	603	505	297	458	355	220	466	347
47	Bank 19	284	868	77	0	1309	0	98	129	284	315	384	328
205	Bank 73	278	114	872	242	0	168	175	120	278	410	116	268
16	Bank 4	222	372	168	301	65	347	404	237	222	281	263	255
24	Bank 8	266	681	175	175	35	292	143	139	266	343	152	254
55	Bank 24	144	313	229	0	1089	0	86	523	144	181	425	250
21	Bank 7	229	226	233	158	197	420	194	167	229	206	244	226
92	Bank 32	250	130	131	0	293	4	183	855	250	87	334	224

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	***Interbank assets***	***Interbank liabilities***	***Securities Outstand.***	***OTC Derivatives***	***Trading & AFS***	***Country Specific Indicator***	***Substitutability***	**Size**	**Interconnectedness**	**Complexity**	
		100.00%	**33.33%**	**33.33%**	**33.33%**	**25.00%**	**25.00%**	**25.00%**	**25.00%**	**33.33%**	**33.33%**	**33.33%**	
36	Bank 12	162	174	149	0	502	0	309	688	162	108	375	215
33	Bank 11	211	152	161	150	193	341	439	118	211	155	273	213
72	Bank 29	56	97	143	0	406	0	145	1228	56	80	445	194
18	Bank 5	210	159	165	104	55	0	355	247	210	143	164	173
446	Bank 81	139	119	353	40	25	508	134	78	139	171	186	165
431	Bank 79	111	168	108	126	39	628	139	104	111	134	228	158
50	Bank 20	148	296	329	15	333	0	12	43	148	213	97	153
115	Bank 37	125	216	462	139	0	55	98	64	125	272	54	151
51	Bank 21	130	40	165	0	429	194	155	114	130	68	223	140
28	Bank 10	152	39	70	13	170	0	230	67	152	40	117	103
218	Bank 75	108	59	248	99	31	10	107	49	108	136	50	98
37	Bank 13	29	164	16	0	636	0	36	47	29	60	180	90
53	Bank 23	99	172	41	0	153	0	37	48	99	71	60	77
456	Bank 82	95	92	39	0	0	109	200	61	95	44	93	77
116	Bank 38	57	127	63	7	0	288	62	37	57	65	96	73
66	Bank 28	60	42	39	0	362	7	59	32	60	27	115	67
571	Bank 113	32	124	60	11	0	342	14	15	32	65	93	63
62	Bank 27	34	88	121	0	287	0	16	21	34	70	81	62
	Dec-17												
13	Bank 2	1336	903	746	1871	1161	1462	833	1134	1336	1173	1147	1219
7	Bank 1	1333	556	963	2304	287	877	1747	552	1333	1274	865	1158
19	Bank 6	1028	815	164	2724	409	1842	777	875	1028	1234	976	1079
14	Bank 3	849	658	646	813	553	943	811	583	849	706	723	759
27	Bank 9	359	242	264	208	660	632	263	518	359	238	518	372
47	Bank 19	271	811	49	0	1350	0	80	129	271	287	390	316
16	Bank 4	210	357	213	292	99	325	577	199	210	288	300	266
205	Bank 73	307	109	783	276	0	102	173	137	307	389	103	266
24	Bank 8	261	635	195	173	60	219	146	155	261	334	145	247
55	Bank 24	138	264	180	0	867	0	98	514	138	148	370	219
21	Bank 7	222	230	187	117	248	405	196	164	222	178	253	218
33	Bank 11	218	147	151	152	240	323	460	115	218	150	285	218
92	Bank 32	223	114	136	0	307	0	147	827	223	84	320	208
36	Bank 12	163	180	112	0	390	0	335	691	163	97	354	205
72	Bank 29	51	88	92	0	325	0	149	1302	51	60	444	185
18	Bank 5	207	200	183	103	67	39	369	213	207	162	172	180

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	*Interbank assets*	*Interbank liabilities*	*Securities Outstand.*	*OTC Derivatives*	*Trading & AFS*	*Country Specific Indicator*	*Substituta bility*	Size	Interconnected ness	Complexity	
		100.00%	33.33%	33.33%	33.33%	25.00%	25.00%	25.00%	25.00%	33.33%	33.33%	33.33%	
431	Bank 79	116	342	165	115	30	522	120	96	116	207	192	172
115	Bank 37	125	251	614	129	0	49	91	83	125	331	56	171
50	Bank 20	172	333	330	12	341	0	12	43	172	225	99	165
51	Bank 21	124	39	185	0	497	170	173	122	124	75	240	146
446	Bank 81	127	155	274	29	34	403	94	81	127	153	153	144
28	Bank 10	143	67	63	10	194	0	239	76	143	47	127	105
218	Bank 75	100	54	246	80	48	9	107	52	100	127	54	94
116	Bank 38	59	142	57	6	0	406	51	49	59	68	127	85
37	Bank 13	33	156	12	0	546	0	44	42	33	56	158	82
53	Bank 23	99	156	40	0	181	0	36	41	99	66	65	76
456	Bank 82	97	73	37	0	0	71	191	66	97	37	82	72
66	Bank 28	60	45	49	0	397	0	53	31	60	31	120	71
169	Bank 71	81	106	121	0	57	21	51	22	81	76	38	65
62	Bank 27	34	78	114	0	309	0	27	25	34	64	90	63
	Jun-18												
13	Bank 2	1313	829	841	1858	1053	1666	844	1150	1313	1176	1178	1222
7	Bank 1	1304	647	924	2260	326	786	1857	542	1304	1277	878	1153
19	Bank 6	1044	863	194	2856	379	1842	723	1051	1044	1304	999	1116
14	Bank 3	843	651	633	819	719	1306	841	539	843	701	851	798
27	Bank 9	355	303	221	179	522	677	290	521	355	234	503	364
47	Bank 19	296	845	66	0	1336	0	90	130	296	304	389	330
205	Bank 73	303	95	896	272	0	83	182	128	303	421	98	274
16	Bank 4	206	306	236	323	101	272	402	220	206	288	249	248
92	Bank 32	226	212	171	0	327	0	165	877	226	128	342	232
33	Bank 11	232	162	255	127	235	341	421	116	232	181	278	230
36	Bank 12	170	237	171	0	387	0	311	707	170	136	351	219
21	Bank 7	210	216	219	102	412	251	175	157	210	179	249	213
55	Bank 24	139	214	142	0	910	0	76	513	139	119	375	211
24	Bank 8	241	426	77	182	54	201	139	129	241	228	131	200
18	Bank 5	214	171	198	85	101	78	393	214	214	151	197	187
72	Bank 29	54	109	103	0	381	0	135	1200	54	71	429	184
50	Bank 20	178	348	297	7	323	0	15	58	178	217	99	165
51	Bank 21	157	61	206	0	480	160	160	143	157	89	236	161
431	Bank 79	112	138	142	130	24	539	138	100	112	137	201	150
115	Bank 37	121	214	473	106	0	48	90	80	121	265	54	147

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	*Interbank assets*	*Interbank liabilities*	*Securities Outstand.*	*OTC Derivatives*	*Trading & AFS*	*Country Specific Indicator*	*Substituta bility*	Size	Interconnected ness	Complexity	
		100.00%	33.33%	33.33%	33.33%	25.00%	25.00%	25.00%	25.00%	33.33%	33.33%	33.33%	
28	Bank 10	144	95	54	11	201	0	204	62	144	53	117	105
218	Bank 75	101	68	253	105	45	8	129	49	101	142	58	100
53	Bank 23	111	197	58	0	179	0	34	46	111	85	65	87
446	Bank 81	104	115	169	23	8	34	75	70	104	102	47	84
37	Bank 13	33	152	50	0	494	0	47	42	33	67	146	82
116	Bank 38	51	104	46	5	1	406	52	36	51	52	124	76
456	Bank 82	99	68	34	0	0	17	246	70	99	34	83	72
66	Bank 28	38	54	59	0	387	0	30	28	38	38	111	62
102	Bank 36	86	14	105	114	0	15	21	54	86	78	23	62
119	Bank 41	67	176	25	54	0	0	79	35	67	85	28	60
	Dec-18												
13	Bank 2	1336	903	746	1871	1161	1462	833	1134	1336	1173	1147	1219
7	Bank 1	1333	556	963	2304	287	877	1747	552	1333	1274	865	1158
19	Bank 6	1028	815	164	2724	409	1842	777	875	1028	1234	976	1079
14	Bank 3	849	658	646	813	553	943	811	583	849	706	723	759
27	Bank 9	359	242	264	208	660	632	263	518	359	238	518	372
47	Bank 19	271	811	49	0	1350	0	80	129	271	287	390	316
16	Bank 4	210	357	213	292	99	325	577	199	210	288	300	266
205	Bank 73	307	109	783	276	0	102	173	137	307	389	103	266
24	Bank 8	261	635	195	173	60	219	146	155	261	334	145	247
55	Bank 24	138	264	180	0	867	0	98	514	138	148	370	219
21	Bank 7	222	230	187	117	248	405	196	164	222	178	253	218
33	Bank 11	218	147	151	152	240	323	460	115	218	150	285	218
92	Bank 32	223	114	136	0	307	0	147	827	223	84	320	208
36	Bank 12	163	180	112	0	390	0	335	691	163	97	354	205
72	Bank 29	51	88	92	0	325	0	149	1302	51	60	444	185
18	Bank 5	207	200	183	103	67	39	369	213	207	162	172	180
431	Bank 79	116	342	165	115	30	522	120	96	116	207	192	172
115	Bank 37	125	251	614	129	0	49	91	83	125	331	56	171
50	Bank 20	172	333	330	12	341	0	12	43	172	225	99	165
51	Bank 21	124	39	185	0	497	170	173	122	124	75	240	146
446	Bank 81	127	155	274	29	34	403	94	81	127	153	153	144
28	Bank 10	143	67	63	10	194	0	239	76	143	47	127	105
218	Bank 75	100	54	246	80	48	9	107	52	100	127	54	94
116	Bank 38	59	142	57	6	0	406	51	49	59	68	127	85

ID	Name	Individual Scores								Sub-Indicators			Systemic Score
		Total Exposure	***Interbank assets***	***Interbank liabilities***	***Securities Outstand.***	***OTC Derivatives***	***Trading & AFS***	***Country Specific Indicator***	***Substitutability***	**Size**	**Interconnectedness**	**Complexity**	
		100.00%	**33.33%**	**33.33%**	**33.33%**	**25.00%**	**25.00%**	**25.00%**	**25.00%**	**33.33%**	**33.33%**	**33.33%**	
37	Bank 13	33	156	12	0	546	0	44	42	33	56	158	82
53	Bank 23	99	156	40	0	181	0	36	41	99	66	65	76
456	Bank 82	97	73	37	0	0	71	191	66	97	37	82	72
66	Bank 28	60	45	49	0	397	0	53	31	60	31	120	71
169	Bank 71	81	106	121	0	57	21	51	22	81	76	38	65
62	Bank 27	34	78	114	0	309	0	27	25	34	64	90	63