Essays on Solvency and Liquidity Using Financial Networks

A thesis submitted for the award of the degree of

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by

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Dedicated to my mom, my father and my sister, whose unconditional support, sacrifices, and endless encouragement have made this long journey possible.

Declaration

I declare that this thesis submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

This thesis sheds light on solvency and liquidity issues using financial networks in both a domestic economy and an international financial market. Chapters 2 and 3 of the thesis focus on analyzing systemic risk in cross-border banking system using the network-based eigen-pair method that treats network failure as a dynamical system stability problem. The quarterly balance sheet data is used to construct the so-called stability network of the Core Global Banking System (CGBS) for 19 BIS countries in the span of 2005 to 2020. Our findings confirm the ability of the method in providing early warning signals for the 2008 Global Financial Crisis (GFC) and highlight the instability of the banking system network for the post-GFC throughout the sample period and finally, call for the necessity of remedial actions. The thesis also identifies systemically important and vulnerable banking systems using network centrality metrics to address the contribution of each banking system to the network and show the threatening role of the US, UK, and Spanish banking systems and the possible consequences of their failure in the international banking system. While the second and third chapters focus on the global banking system, Chapter 4 investigates liquidity dynamics in the domestic US economy, highlighting the importance of comprehending liquidity for financial stability. The research utilizes the Structural Vector Autoregression (SVAR) model to analyze causal relationships and capture complex liquidity dynamics in the US economy. The study emphasizes the significance of disruptions in debt payments by firms and the role of the money market in financing current liabilities. The findings show the crucial role of the quick ratio and network effect in the economy's business cycle compared to other variables. Policymakers, regulators, and market participants can utilize these insights to manage liquidity risks effectively and establish resilient frameworks to promote market stability.

Contents

Declaration

Acknowledgements

Abstract

Contents

List of Figures

List of Tables

1 Introduction **1**

2 Solvency Contagion Analysis for Global Banking System Using Financial Network **6**

2.1 Introduction 7
2.2 Literature Review 11
2.3 Methodology 16
2.3.1 Financial Network Analysis for Cross Border Model 16
2.3.2 Contagion and Network Stability Analysis 18
2.4 Data 22
2.5 Empirical Results 26
2.5.1 Country Cross-border Analysis 26
2.5.2 Cross-border Network Analysis 31
2.5.3 Contagion Analysis 41
2.6 Conclusion 45

3 Liquidity Contagion Analysis for Global Banking System Using Financial Network **48**

3.1 Introduction 49
3.2 Literature Review 51
3.3 Methodology and Data 55

3.3.1 Financial Network Analysis for Cross Border Model . . . 56
3.3.2 Network Stability Analysis . . . 58
3.3.3 Data . . . 60
3.4 Empirical Results: Cross-border Network Analysis . . . 64
3.5 Concluding Remarks . . . 69

4 The Origin of Aggregate Fluctuation in a Network Economy: Liquidity Issue 71
4.1 Introduction . . . 72
4.2 Related Literature . . . 76
4.2.1 Liquidity and Business Cycles . . . 76
4.2.2 Structural VAR Model . . . 79
4.3 Data and Empirical Model . . . 82
4.3.1 Data Discription and Choice of Variables . . . 82
4.3.2 Structural Vector AutoRegressive (VAR) model . . . 98
4.3.2.1 Model Setup . . . 99
4.3.2.2 The Identification Problem . . . 99
4.3.2.3 Model Specification . . . 104
4.3.2.4 Impulse-Response Functions (IRFs) . . . 105
4.3.2.5 Forecast Error Variance Decompositions (FEVD) . . . 106
4.4 Empirical Results . . . 106
4.4.1 Model Specification . . . 107
4.4.2 Impulse Response Functions (IRFs) Analysis . . . 109
4.4.3 Analysis of Forecast Error Variance Decomposition (FEVD) . . . 113
4.5 Concluding Remarks . . . 119

5 Contributions and Concluding Remarks 122

A *Complementary Materials for Solvency and Liquidity Analysis in Cross-border Banking System* 125
A.1 Annex A - Instruction for cross border data using BIS Consolidated Banking Statistics (CBS) . . . 125
A.2 Annex B - Adjustment of the data for cross-border banking system network: . . . 128
A.3 Annex C - Tier 1 capital . . . 130
A.4 Annex D - Total gross foreign claims/liabilities . . . 133
A.5 Annex E - Network statistics . . . 134
A.6 Annex F - Cross-border banking systems exposures . . . 137
A.7 Annex G - Node statistics . . . 138
A.8 Annex H - Total global and domino losses. . . . 139
A.9 Annex G - Motivations and literature review . . . 139
A.9.1 Solvency Issue . . . 139
A.9.1.1 Solvency Issue in Cross Border Setting . . . 140
A.9.1.2 Financial Networks . . . 144

A.9.2 Liquidity Issue . . . 149
A.9.2.1 Literature Review . . . 149
A.9.2.2 Systemic Risk in Global Market . . . 152
A.9.2.3 Liquidity Issue in Cross Border Setting . . . 161

B *Complementary Materials for Liquidity Origins of Aggregate Fluctuations* 165
B.1 Network Centralities . . . 165
B.2 The Hodrick and Prescott (HP) Filter . . . 168
B.2.1 Summary Statistics Table . . . 170
B.3 Model Specification . . . 171
B.3.1 The AR model selection criteria . . . 171
B.3.2 Augmented Dickey Fuller (ADF) unit root tests . . . 172
B.4 Model Diagnostics . . . 172
B.4.1 Stability Test for VAR model . . . 173
B.4.2 Structural Break . . . 174
B.4.3 Residual Analysis . . . 175
B.4.4 Sensitivity Analysis . . . 181
B.4.4.1 Model Parameters . . . 181
B.4.4.2 Model Covariance Matrix . . . 182
B.4.4.3 Forecast Error Variance Decomposition (FEVD) . . . 185

Bibliography 188

List of Figures

2.1 Adjusted Tier 1 capital time series of BIS reporting banks . . . 25
2.2 Aggregated adjusted Tier 1 capital time series of 19 BIS reporting banks . . . 26
2.3 Total net foreign liabilities of BIS reporting banks . . . 28
2.4 Aggregated gross foreign liabilities of 19 BIS reporting banks . . . 29
2.5 Cross-border banking systems exposures of the top lenders . . . 30
2.6 Network visualization for the cross-border bilateral exposures . . . 33
2.7 Statistical network analysis . . . 36
2.8 Connectivity and network instability index . . . 37
2.9 Dynamic of Systemic Importance Index of Cross-border Banking Systerms . . . 40
2.10 Dynamic of Systemic Vulnerability Index of Cross-border Banking Systerms . . . 41
2.11 Contagion Process in Response to the US Banking System Failure . . . 43
2.12 Total loss of capital for the BIS cross-border banking systems . . . 45

3.1 High-quality liquid assets time series . . . 61
3.2 Short-term liabilities time series . . . 62
3.3 Encumbered Liquidity ratio time series . . . 64
3.4 Connectivity and network instability indices . . . 66
3.5 Dynamic of systemic importance (right eigenvector centrality) . . . 67
3.6 Dynamic of vulnerability index (left eigenvector centrality) . . . 69

4.1 Time Series of Quick Ratio . . . 85
4.2 Weighted Degree Distribution . . . 90
4.3 Time series of the Network Index . . . 93
4.4 Time Series of Repo Rate . . . 94
4.5 Time series of GDP . . . 95
4.6 Exogenous Variables time series . . . 98
4.7 SVAR Impulse Response Functions (IRFs) . . . 114
4.8 Forecast Error Variance Decomposition (FEVD) of the variable of interests . . . 117

A.1 Tier 1 capital time series . . . 130
A.2 Aggregated Tier 1 capital time series . . . 131
A.3 Adjustment ratios . . . 132
A.4 Total gross foreign claims . . . 133
A.5 Total gross foreign liabilities . . . 134

A.6 Cross-border banking systems exposures to the top borrowers 137
A.7 Policy rates for the Federal Reserve, Bank of England, and Bank of Japan. . . . 156
A.8 Total central bank assets 157
A.9 Secured overnight financing rate 159
A.10 Geographic Distribution of Total (in million dollars) 164

B.1 Stability Test for VAR model 174
B.2 Stability Test for Structural Breaks 175
B.3 ARCH (Autoregressive Conditional Heteroskedasticity) Test for Heteroskedasticity 178
B.4 Histogram of the Residuals 180

List of Tables

4.1 The best AR lag length order suggested by each criterion . . . 107
4.2 Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/network effect system . . . 118

A.1 Network statistics . . . 138
A.2 Total global and domino losses for the US, UK, and Spain. . . . 139

B.1 Network effect . . . 168
B.2 Applied Variables and Summary of their Statistics . . . 170
B.3 The AR model selection criteria . . . 171
B.4 ADF unit root tests for the time series variables of interest . . . 172
B.5 Results of the Box-Ljung Test . . . 176
B.6 Results of the Portmanteau Test (asymptotic) . . . 177
B.7 Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/network effect system for AB model . . . 185
B.8 Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/mean degree system . . . 186
B.9 Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/variance degree system . . . 187

Chapter 1

Introduction

The thesis discusses the critical role of liquidity in both domestic and global financial markets. Liquidity plays a fundamental role in lubricating an economy as it refers to how easily an asset can be converted into cash without significant losses in value and can make the economy go round (Tracy and Tracy, 2014; Vernimmen et al., 2022). Similarly, global liquidity plays a crucial role in the functioning of the global economy, where it addresses the availability and ease of access to funds and credit in the international financial system, encompassing various financial flows and cross-border banking system. Global liquidity is critical components of the international financial system and play a significant role in shaping the dynamics of the global economy. In this context, in an economy where firms and financial intermediaries engage in frequent trading using short-term assets and liabilities, examining the sources and the channels of risk that can make the systems unstable and cause fluctuations becomes crucial for financial resilience (Beck et al., 2022).

Having sufficient liquid sources is extremely important for firms to address short-term payment obligations, handle unexpected expenses, manage working capital, effectively respond to changes in market conditions, and ensure that the market functions smoothly. On the other hand, a lack of liquidity can lead to market illiquidity, increased price volatility, and

potential crises (Erel et al., 2021; Jordà et al., 2021). In financial market's transactions and network economic activities, which involve interdependencies and time-sensitive commitments between economic agents, any delays in payment settlements or disruptions in the flow of liquidity can have cascading effects (Gatti et al., 2009; Acemoglu et al., 2012; Carvalho, 2014). These effects can manifest as liquidity problems, credit risks, and even systemic issues within a network economy where firms trade and interact with one another (Acemoglu et al., 2015, 2017; Altinoglu, 2021).

The global financial crisis of 2008 serves as a valid example of how insufficient liquidity can have severe consequences for the financial system and the broader economy. The consequences of not having enough liquidity were not restricted only to the US real estate and spread through the entire economy but also created a ripple effect throughout the whole international financial system due to the interconnected nature of cross-border lending and financial derivatives amplified the contagion effects, rapidly spreading distress from one region to another. The need to model financial interconnectedness and the potential for systemic risk became evident, emphasizing the importance of analyzing global liquidity within the context of a financial network (Gorton, 2008, 2009; Lou and Sadka, 2011).

This study aims to shed light on the role of liquidity in the stability of both a domestic economy as well as the international banking system using financial networks. We attempt to have a bottom-up view of the components of the economy, both domestically and internationally, with the help of network analysis. Financial network analysis received intensive scrutiny after the Global Financial Crisis (GFC) in 2007-8 when many traditional standard economic models were not able to predict the crisis. Following the GFC, researchers address the topology of networks of banking systems to prevent financial fragility as it could model the interconnectedness of the financial system to include the threat of financial contagion (Haldane, 2013). Today, network models can provide a robust framework to analyze a system as a whole so that we have a relatively complete perception of the complex system and its corresponding economic components.

The second and third chapters of this thesis applied the network approach to assess systemic risk and financial contagion in cross-border banking systems based on Markose (2012) and Markose et al. (2021). More specifically, Chapter 2 exploits the financial network topology to discuss the solvency issue for BIS consolidated banking data. The study implements empirical analyses on national banking systems and their associated systemic risks, employing the eigen-pair method with real-world data from 2005 to 2020 sourced from the Bank for International Settlements (BIS) and the International Monetary Fund (IMF). The chapter chooses the spectral eigen-pair Systemic Risk Index (SRI) over the popular market price-based SRIs like Marginal Expected Shortfall (MES), Delta Conditional Value-at-Risk (ΔCoVaR), and Conditional Capital Shortfall Measure of Systemic Risk (SRISK) proposed by Acharya et al. (2012, 2017) and Adrian and Brunnermeier (2011). The choice stems from the inefficiency of the latter indices in capturing the risk and offering early warning signals prior to a crisis (Minsky, 1977; Borio and Drehmann, 2009; Markose, 2012). Following a growing literature on contagion and cascade models, the spectral eigen-pair method, inspired by epidemiology, has been notably overlooked from modeling financial contagion in systemic risk analysis (Wang et al., 2003; Chakrabarti et al., 2008). This method, introduced by Markose (2012, 2013), relies on two fundamental causal factors: the transmission rate of infection and the cure rates. These factors are instrumental in developing the systemic risk index and conducting financial contagion analysis. In the realm of financial contagion, the "infection rates" refers to financial exposure rates, representing the extent of exposure of a financial institution to potential risks from creditors. The "cure rate" also addresses the rate of the capital that can mitigate the propagation of losses within credit chains in a financial market, particularly when contagion arises from insolvency and illiquidity (Markose et al., 2021).

The Chapter 3 contributes to the existing literature by extending the second chapter and employing financial network analysis to explore global liquidity within the cross-border banking system. The first contribution of this part is to provide insights into the current state of global liquidity and the potential risks of liquidity crunch episodes. This analysis warns policymakers

about the inadequately observed nature of global liquidity, emphasizing the need for effective management to mitigate negative spillovers and enhance financial system resilience. Another contribution of this chapter lies within the realm of network analysis by developing the eigen-pair method and introducing the systemic risk index that considers not only the solvency risk but also the liquidity risk. The aim is to provide financial leaders and regulators with a comprehensive understanding of systemic risk and the potential contagion processes that occur when a banking system fails. Additionally, the research classifies the systemic importance and vulnerability of banking systems in different countries using eigenvector centrality measures.

While the second and third chapters attempt to analyze the systemic risk in the international banking system, the fourth chapter mainly focuses on the analysis of liquidity in a domestic US economy and assesses the origins of aggregate fluctuations in a network economy that can arise from *liquidity shortage* and corresponding forces. For this purpose, Chapter 4 considers a network economy in which firms hold part of the short-term assets to pay for their current debt and then exchange the other part of their internal short-term resources to trade intermediate goods. Firms are also able to enter the money market to borrow additional resources in order to pay off their debts or purchase their inputs. In such an environment, any disruption in the ability of firms to meet their short-term liabilities can generate financial and monetary shocks not only to the firm's internal resources but also to the interlinkages between firms. This part has shed light on the cascading effects that liquidity disruptions and their corresponding movements can have within a network economy. We use the Structural Vector Autoregression (SVAR) model to examine the liquidity dynamics in the U.S. economy and analyze the interactions between liquidity-related variables. To do this, the liquidity data are initially directly derived from the balance sheets of the top 100 large firms according to the $S\&P100$ index during the years $2006Q1$ to $2020Q4$. The research also identifies the relevant shocks of the variables of interest and describes the response of the system to each structural innovation through the Impulse Response Functions (IRFs). We also investigate the importance of each shock by reporting the proportion of each innovation over the whole system by decomposing the Forecast Error

Variances (FEVs).

In conclusion, this thesis seeks to enhance our understanding of liquidity within the cross-border banking system and the U.S. economy. This research contributes to the ongoing efforts to monitor and manage liquidity risks by examining the stability of the national and international systems, identifying important corresponding forces, and exploring the vulnerabilities associated with them. The analysis conducted in this study offers valuable insights for policymakers and regulators, ultimately aiming to strengthen the resilience of the system. The structure of this thesis is as follows; In Chapter 2 and Chapter 3, we conduct respectively the solvency and liquidity contagion analysis for Global Banking System using financial network. Chapter 4 illustrates the liquidity origin of aggregate fluctuation in a network economy, and finally, Chapter 5 concludes the achievement of the thesis.

Chapter 2

Solvency Contagion Analysis for Global Banking System Using Financial Network

Abstract. This chapter examines systemic risk in the core international banking system using the network-based eigen-pair method in contrast to the common market price-based Systemic Risk Indexes (SRIs). In this study, the quarterly balance sheet data of the cross-border banking system are used to construct the generalised stability network of the Core Global Banking System (CGBS) for 19 reporting BIS countries in the span of 2005 to 2020. Our findings show the early warning signal for the Global Financial Crisis (GFC) in 2007-2008 and highlight the inherent instability of the global banking system throughout the whole sample period. Furthermore, the chapter identifies systemically important and vulnerable banking systems using network eigenvector centrality metrics. Our results show the threatening role of the US, UK, and Spanish banking systems, and the possible consequences of the failure of these banking systems in the international banking system.

Keywords: Financial network, systemic risk, eigen-pair method, early warning signal, cross-border banking system, solvency analysis.

2.1 Introduction

Global Financial Crisis (GFC) in 2007-2008 marked a pivotal moment in financial resilience research, emphasizing the importance of systemic risk analysis and macro-prudential policies. Several studies questioned the efficacy of systemic risk indices and their ability to capture the risk and provide early warning signals for crises.[1] The role of cross-border exposures in the dynamics of the GFC was also underscored when the European banks had surprisingly large exposure to the US securitized assets and then resulted in a 50% equity capital loss (valued at $1.6 trillion) (Allen, 2011; Calabrese and Osmetti, 2019). Accordingly, some addressed the critical role of interdependencies among Financial Institutions (FIs) and the potential for contagion to amplify the impact of financial crises. These discussions underscore the need for sound financial health and adequate capital reserves in the face of crisis.

Hence, in the aftermath of the 2008 crisis and the destructive effects of systemic financial risk in the following decade, when many traditional econometric and standard macroeconomic models were not able to predict the crisis, the analysis of systemic risk and macro-prudential has come up to the forefront to monitor, manage, and model the negative externalities that can arise from each component of a system and can end up in the failure and instability of the system (Brunnermeier et al., 2009; Duarte and Eisenbach, 2021). While traditional finance has viewed risk mainly from a market price data point of view, financial network analysis has received a lot of attention, and researchers tried to examine the topology of networks of banking systems to not only look closely into the elements of the complex financial system, but also to have a relatively complete perception of the complex dependencies between economic components (Haldane, 2013).[2] Furthermore, economists have increasingly adopted an epidemiology-inspired

[1] Bisias et al. (2012) and Iván et al. (2016) give an extensive discussion about the lack of consensus on measuring systemic risk. Additionally, see Kou et al. (2019) about the latest systemic risk methods.

[2] Haldane (2013) drew attention to the need of modeling the interconnectedness of the financial system to include the threat of financial contagion in the wake of the collapse of large financial institutions like AIG and Lehman Brothers. There are studies still highlighting and warning about the role of the interconnected nature of financial systems after Haldane (2013). Giudici et al. (2020) and Raddant and Kenett (2021) is one of the most recent studies about the interconnectedness in the financial market.

approach to examine systemic risk within interconnected networks. Some connections have also been made between the dynamics of financial contagion and epidemic models (Wang et al., 2003; Chakrabarti et al., 2008; Newman, 2018). Notably, researchers have actively explored concepts like tipping points in measuring the risk in financial networks, a notion popularized by Furfine (2003). Markose (2012, 2013) also proposed the eigen-pair method, which relies on the tipping point and bears similarities to the Reproductive (R) number in epidemic models (Van den Driessche, 2017).

Similarly, in this chapter, the balance sheet network-based spectral Systemic Risk Index (SRI) is selected over the popular market price-based SRIs to assess systemic risk and contagion in global solvency, such as Marginal Expected Shortfall (MES), Delta Conditional Value-at-Risk (ΔCoVaR), and Conditional Capital Shortfall Measure of Systemic Risk (SRISK) that are mainly introduced respectively by Acharya et al. (2012, 2017) and Adrian and Brunnermeier (2011). These market price-based indices suffer from the so-called "paradox of volatility" that is similar to the volatility of asset returns, which appears the risk at lowest just before the crisis. This was addressed initially by Minsky (1986) and then applied by Borio and Drehemann (2010) and other economists, such as Brunnermeier and Sannikov (2015) and Markose (2013).[3] Later on, in post-GFC, several studies have identified the asset bubbles as a major driver of failure in financial institutions (see Glasserman and Young (2015); Bruno and Shin (2015a); Glasserman and Young (2015); Bruno and Shin (2015a); Schularick and Taylor (2012)).[4] Finally, several studies such as Benoit et al. (2013, 2017) suggest the market price-based risk indices exhibit a positive correlation with market returns, rather than functioning as systemic risk indicators that identify tipping points leading to widespread system failures.

[3] Minsky (1986) for the first time before the GFC mentioned the problem of asset returns volatility. He warned that asset bubbles mask the growing fragility of the financial system as they inflate market values for assets that can create the illusion of low risk that is gained from paradoxical volatility measures and encourage procyclical excessive expansion of leverage of banking systems. This growth extends to interbank exposures and liabilities, encompassing non-bank sectors as well.

[4] Borio et al. (2001) extensively discuss this problem of procyclicality and the underestimated potential for system failure using market price-based systemic risk indicators (SRIs).

Compared to market price data, especially in terms of volatility modeling, which can be blindsided by increased leverage during an asset price surge that paradoxically shows low volatility in asset market returns, we utilize the capabilities of the balance sheet network-based Spectral SRI to analyze systemic risk in the core global banking system. The Spectral SRI addresses concerns regarding the paradoxical nature of market price risk indices by leveraging real-world liability data via financial networks for systemic risk modeling, particularly when weaknesses in financial institutions' balance sheets stem from growing liabilities to counterparties (Minsky, 1977; Borio and Drehmann, 2009; Markose, 2012). Furthermore, we employ the eigen-pair method, inspired by epidemiology, for modeling financial contagion in systemic risk analysis. This method, introduced by Markose (2012, 2013), relies on two key causal factors identified in the epidemiology literature. The method adopts the transmission rate of infection and cure rates to develop the systemic risk index and conduct financial contagion analysis (see, May (1972); Wang et al. (2003); Markose (2012); Markose et al. (2012); Bardoscia et al. (2017); Newman (2018)). In the context of financial contagion, the 'infection rates' refers to financial exposure rates, where the exposures of a FI can arise from creditors. This exposure can be reflected by the amount of debt held by each counterparty within the interconnected structure of the financial market, which ultimately drives the cascade of defaults among debtors. In a financial market where the contagion stems from insolvency, regulatory capital serves as a safeguard and mitigates the propagation of losses within credit chains. This role resembles the function of immune responses that contribute to cure rates in epidemic models. This approach in eigen-pair method is consistent with the Reproductive (R) number in epidemiology, where the R number specifies that the transmission of infection in the population increases exponentially if it is greater than threshold 1 (Van den Driessche, 2017; Markose et al., 2021).

This research intends to assess systemic risk and contagion in cross-border banking system using financial networks to address the potential risks and vulnerabilities in the international banking system. The main contribution of this chapter is threefold. Firstly, it utilizes financial network topology and the network-based eigen-pair method to analyze the solvency concerns

within the 19 Core Global Banking System (CGBS) from 2005 to 2020. Employing real-world balance sheet data obtained from the Bank of International Settlements (BIS), this empirical analysis examines national banking systems' interconnections and systemic risk using the eigen-pair method. This method gauges systemic risk by evaluating spectral stability features of financial contagion, signaling potential contagion spread when the maximum eigenvalue surpasses a defined capital threshold. The method hinges on the maximum eigenvalue of the constructed generalised stability matrix adjusted by counterparties' net liabilities and regulatory capital. The Spectral SRI is bound by an upper limit set by the maximum row sum (infinity norm) of the stability matrix, reflecting network positions and leveraging of participants, wherein a single highly leveraged member significantly impacts system instability. It explains that for financial stability, the stability matrix's maximum eigenvalue should stay below the capital loss threshold, aligning with the concept that the cure rate should exceed the infection rate in controlling an epidemic.

The second contribution of this chapter is to classify the rank order for systemic importance and for systemic vulnerability of the countries' banking systems. We employ the right and left eigenvectors centralities associated with the maximum eigenvalue of the generalised stability matrix to identify the risk contribution of each banking system within the cross-border network. The right and left eigenvector centrality measures correspond to the most systemically important and vulnerable indices. The right eigenvector centrality provides a numerical ranking of the banking systems' systemic importance based on their potential to cause capital loss if they fail. Meanwhile, the left eigenvector offers a ranking of banking systems' susceptibility to contagion and the estimated percentage of capital loss they might experience. Finally, we analyze the contagion process of the model to predict the capital loss and repercussions in a scenario where one of the systemically important banking systems fails to meet its obligations. In our empirical model, we use BIS Consolidated Banking Statistics from the BIS organization for both the exposures and debtors of 19 international banking systems and also the Tier 1 capital for the same countries obtained from the International Monetary Fund (IMF) database.

The structure of this chapter is as follows; In Section 2.2 we review the literature for the cross-border model and financial network. The methodology and the data are elaborated in Section 2.3 and 2.4, respectively. Section 2.5 illustrates the empirical results, and finally, Section 2.6 encompasses the achievement of the chapter.

2.2 Literature Review

The long-lasting impact of the 2008 financial crisis on the global economy opened a serious debate about the origins of the crisis and spillovers to the integrated international financial system. One of the critical factors that triggered the financial meltdown in GFC were Collateralized Debt Obligations (CDOs) and Mortgage-Backed Securities (MBSs) backed by non-prime loans.[5] The issuance of CDOs, particularly subprime MBSs, grew considerably during 2003-2007, and credit rating agencies failed to estimate the true risk of these securities accurately, and in turn overrated them by marking them falsely as "safe assets" with a high rate of AAA. The regulated and authorized Financial Institutions (FIs) issued loans, which were secured by claims against mortgagors' purchases, and highly leveraged firms invest heavily in CDOs, in particular those backed by subprime MBSs as collateral. The collapse of collateral prices in late 2007 generated huge loan defaults, causing significant disruptions in both banks and shadow banking systems. This generates significant losses for institutional investors and FIs, who intended to invest in high-yielding AAA securities and ultimately contributed to one of the worst global systemic crises in 2008 (Chernenko et al., 2014; Ospina and Uhlig, 2018; Adelino et al., 2018).

The bursting of a housing bubble in the US real estate market transmitted globally and led to the GFC and has underlined the importance of banking system stability from the cross-border propagation of contagion point of view. The high exposure of European banks to the US securitized assets led to a 50% equity capital loss (i.e., around $1.6 trillion) underscored the role

[5] Collateralized Debt Obligations (CDOs), most notably subprime MBSs, are both classes of Assest-Back Securitization (ABS) backed by non-prime loans.

of cross-border exposures in the dynamic of the 2008 crisis, and sheds light on the pivotal role of interconnectedness within the financial network, paving the way for systemic risk analysis in the financial system, particularly within the global banking system (Soramäki et al., 2007; Bruno and Shin, 2013; Castrén and Rancan, 2014).[6] The cross-border exposure of banks is considered one of the main drivers of the 2008 financial crisis in such an integrated international financial system (Degryse et al., 2010; Allen, 2011; Reyes and Minoiu, 2011; Castrén and Rancan, 2014). Bailing out of main FIs in the UK, US, and Eurozone countries costs over $14 trillion for taxpayers and reinforced academics and regulators to identify, control, and monitor the failure of FIs that arises from the domino effects of illiquidity and insolvency.[7]

There is one strand of studies that shed light on cross-border bank exposure and interconnectedness within the financial network (Cerutti et al., 2012; Castrén and Rancan, 2014). These focus on interdependency among financial institutions that can magnify disruptions, allowing shocks in one segment to propagate widely, causing losses throughout the system. Von Peter (2007) and Minoiu and Reyes (2013) study the topology of global networks using various centrality metrics such as degree, betweenness, closeness, and weighted centrality to discuss the soundness of international banking. Their result shows the global banking network is relatively unstable and reports the structural breaks in the network. Degryse et al. (2010) investigate cross-border exposures of contagion risk and warn on growing systemic risk in the international financial systems for the period 1999-2006. Degryse et al. (2010) also warns about the role of the US banking system that can lead to a destructive contagion effect throughout the international banking system and collapse the entire system (similar studies can be found here: Hattori et al. (2007) and Castrén and Rancan (2014)).[8] This line of research primarily relies on

[6] Additionally, Jackson and Pernoud (2021) present an overview of how modern financial networks relate to systemic risk, introducing a taxonomy of systemic risk categories. Their discussion also provides insights on optimal regulation and bailouts regarding bank's portfolios and partnerships.

[7] Giudici et al. (2020) and Raddant and Kenett (2021) recently highlight the importance of analyzing the structural topology of global banking systems and their vulnerability to the liabilities of debtor sovereigns.

[8] There is also empirical research that studies financial network and investigate other channels of contagion through payment system in the banking system (See more studies in McAndrews and Roberds (1995); Freixas and Parigi (1998); Freixas et al. (2000) and Furfine (2003)). Allen and Gale (2000) focuses on banking systems with different regions and sectors and shows that the optimal solution for banks is to hold liquidity in case of high demand. Besides, one strand of the research discusses currency crises and their international contagion

BIS cross-border banking system data to explore the interconnectivity within the international banking system. We similarly leverage BIS balance-sheet data to analyze and construct the network between banking systems.

Another strand of the literature focuses on the relationship between connectivity and resilience of financial networks. Cabrales et al. (2017) examine how the system's resilience to absorb shocks is intricately tied to the specific network patterns formed among firms. Allen and Gale (2000) show the effect of various network structures in propagating shocks within banks. They discuss that each bank's total exposure is equally divided among its counterparties if the bank's network is complete, and hence risks of failure of each bank and propagation through the system are small. Thus, the whole system can be more stable and resilient compared to an incomplete financial network, where a failure of one bank can result in the failure of the entire system. Similarly, Babus (2016) examines the connectivity and contagion within highly interconnected banks and concludes that higher connectivity can enhance resilience and decrease the risk of contagion. Similar results are also gained by Castiglionesi and Navarro (2007), Freixas et al. (2000), and Gai and Kapadia (2010). Likewise, regulators and researchers warn about the phenomena of "too interconnected to fail" and "too big to fail", where a failure of one FI can lead to a large propagation of failure in the whole system in an interconnected environment (Gofman, 2017; Markose et al., 2012; Bernanke et al., 2010). Elliott et al. (2014) explains the European debt cross-holdings in terms of "too big to fail" phenomena and the cascades of failures within an interconnected network of financial institutions. Volcker (2012) also point out that "the risk of failure of large interconnected firms must be reduced, whether by reducing their size, curtailing their interconnections, or limiting their activities".[9] Moreover,

such as Masson (1999), Eichengreen et al. (1996), and Glick and Rose (1999). Forbes and Rigobon (2002); Pavlova and Rigobon (2008) also provides a theoretical model of contagion that arises from the stock market prices across different countries. There were also studies addressing other factors in aggravating the crisis in the cross-border banking system, such as the carry trade behavior of investors, international capital flows, the unconventional monetary policies in advanced economies, etc. The extensive review of this literature can be found in Section A.9.1.

[9] Cabrales et al. (2016), however, distinguishes literature focused on financial institutions with "special" characteristics, like being considered "too big to fail" or "too interconnected to fail". This research challenges the notion that systemic issues only arise from asymmetry, demonstrating that even symmetric situations can lead to systemic problems.

according to May (2019), connectivity can be a double-edged sword as the impact of connectivity strictly depends on the degree distribution characteristics, taking into account the structure of the network. Battiston et al. (2012) similarly confirm that connectivity and resilience are not a simple monotonic relationship and propose a threshold that beyond, connectivity can raise instability. Although there is no robust consensus on specific structures in networks, all agree on the superiority of merging financial systems and network theory to analyze systemic risk and contagion. Glasserman and Young (2016) review the extensive discussion on the contagion in an interconnected financial system and how it contributes to systemic fragility. They particularly emphasize the interaction between network structure and crucial factors like leverage, size, shared exposures, and short-term funding.

There are also studies addressing the pro-cyclical behavior of connectivity in the global banking system using the market price-based systemic risk criteria, such as Marginal Expected Shortfall (MES), Delta Conditional Value-at-Risk (ΔCoVaR), and Conditional Capital Shortfall Measure of Systemic Risk (SRISK) that are mainly introduced respectively by Adrian and Brunnermeier (2011) and Acharya et al. (2012, 2017).[10] On the contrary, there is a line of studies addressing the inefficiency of these indices and criticizing them for their weak performance. This research primarily critiques market price-based SRI for their inability to provide 'early' warnings, underestimation of risk, paradoxes related to volatility, and other limitations (Borio and Drehmann, 2009; Borio and Drehemann, 2010; Degryse et al., 2010; Adrian and Brunnermeier, 2011; Arsov et al., 2013; Markose et al., 2021).

Several studies have also underscored the marked procyclicality of banking lending, amplifying significantly during economic booms and contracting sharply during crises. These studies also address the substantial impact of bank capital flows, emphasizing how banks structure their balance sheets to manage these effects (Kaminsky et al., 2004; Brunnermeier and Sannikov, 2014, 2015). Some studies try to take advantage of the balance sheet data to extract directly

[10] Adrian and Brunnermeier (2011), Pedersen et al. (2010), Chan-Lau et al. (2009), Huang et al. (2012), Goodhart and Segoviano (2009), Tarashev et al. (2010), Gauthier et al. (2012), and Minoiu and Reyes (2013) are some of the research used market price-based to analyze the systemic risk.

the exposure risk of financial institutions. These studies examine the effectiveness of balance sheet-based models in analyzing systemic risk as opposed to market price data, where market price models can be susceptible to overlooking increased leverage during asset price surges, paradoxically displaying low volatility in the asset market. The Spectral eigen-pair method by Markose (2012) also addresses this issue, aiming to develop a balance sheet-based network model that alleviates concerns related to the paradoxical nature of market price risk indices. This approach is particularly valuable in identifying weaknesses within financial institutions' balance sheets originating from escalating liabilities to counterparties. Similarly, in this research, our goal is to track and monitor the exposure risks faced by creditors concerning debts owed to and by other parties within the interconnected balance sheets of financial institutions (FIs). Our focus is on constructing these interlinkages within the balance sheets of the cross-border banking system. These connections act as catalysts for a ripple effect, whereby the failure of debtors to fulfill obligations triggers cascading impacts on interconnected entities.

Additionally, Eisenberg and Noe (2001) and Gauthier et al. (2012) are among the studies discussing the significance of power iteration fixed-point algorithms in systemic risk analysis. Eisenberg and Noe (2001) utilize the fixed-point algorithm to distribute exogenous losses among all participants within the financial network. This serves as the initial stage of contagion in their models, ensuring that the losses incurred by one participant maintain internal consistency in line with others. Gauthier et al. (2012) similarly emphasize the pivotal role of fixed-point algorithms in systemic risk analytics, emphasizing their capacity to maintain a high level of internal consistency that aligns with extensive interconnections. Likewise, Markose (2012) used the power iteration fixed-point algorithms and the epidemic literature to suggest an SRI based on the concept of eigenvalue and corresponding eigenvector centralities.[11] Markose et al. (2021)

[11]Google's PageRank, Katz, and Bonacich centrality are variants of eigenvector centrality (see Brin and Page (1998), Katz (1953), and Bonacich (1987)). The advantage of using the eigenvector metric over others is that the concept of eigenvalue and its associated left and right eigenvector centralities allow us to extract more information about the positions of nodes within a network. Section 2.3 explains more details about the role of right and left eigenvectors in determining important and vulnerable nodes within our cross-border banking system.

later documented the efficiency of the eigen-pair method SRI compared to other market price-based SRIs. This chapter applied the same method for 19 banking systems for the period 2005 to 2020 and checked for the contagion process in the cross-border banking system.

All these issues have brought up the discussion over the inadequacy of global financial systems and have underscored the necessity of employing comprehensive systemic risk indices to investigate the components primarily responsible for the system's instability (Ghymers, 2017; Icard and Turner, 2019). Prior to considering possible policies in managing global solvency, cross-border financial networks should be modeled to explain systemically important financial intermediaries and the vulnerability of the countries. The aim of this research is to contribute to the literature by analyzing the network topology of the core global banking system, identifying the most systemically important and vulnerable banking system within the global network, and testing for contagion spillovers.

2.3 Methodology

This section highlights two theoretical parts of studying cross-border banking networks. The first part elaborates on our approach to constructing the financial network analysis for the cross-border model as well as the statistics for characterizing the network topology. The second part then explains the framework for the contagion and stability analysis of the system.

2.3.1 Financial Network Analysis for Cross Border Model

The first step to analyzing the cross-border banking system is to build a network for tracing the payment circulation. Any network contains N number of nodes (vertices) which are connected by E set of linkages (pair of finite sets (N, E)). Financial networks are generally directed weighted networks in which every banking system from BIS reporting countries in this

study is represented as one node and each link is determined by directional bilateral relationship (borrowing/lending) between nodes (Degryse et al., 2010). The following matrix 2.1 is a sample characterization of our network,

$$X = \begin{pmatrix} 0 & x_{12} & ... & ... & ... & x_{1N} \\ x_{21} & 0 & ... & ... & ... & : \\ : & : & 0 & ... & ... & : \\ : & : & : & 0 & ... & : \\ : & : & : & : & 0 & x_{iN} \\ x_{N1} & : & : & : & x_{Nj} & 0 \end{pmatrix} \tag{2.1}$$

where a gross flow of claims in the above $N \times N$ matrix is constructed and each element x_{ij} is the direct link and reflects the flows of claims (liabilities) from FI i to counterparty j. These links or edges are also known as out-degree and in-degree linkages which indicate respectively the flow of claims (payments or financial obligations) to and from each FI (Harary et al., 1965; Eisenberg and Noe, 2001; Albert and Barabási, 2002; Newman, 2003). According to matrix X, Equation 2.2, G_i and B_j are also defined respectively as row sum and column sum of the matrix X,

$$\begin{aligned} G_i &= \sum_j x_{ij} \\ B_j &= \sum_i x_{ij} \end{aligned} \tag{2.2}$$

where the former represents the total foreign liabilities of the country's banking system across other countries' banking systems, and the sum of columns gives the total gross foreign claims of the banking system j over the rows i. The diagonal is also zero since no FI is able to lend or borrow themselves (Markose, 2013; Markose et al., 2021). Based on matrix X, the netted matrix M can be constructed that is a "skew-symmetric matrix" with entries $m_{ij}^{+} = m_{ij}^{-}$. Each m_{ij} in matrix M shows the netted position between bank i and its corresponding counterparty

j. If an entry m_{ij} is positive, there exists a net financial claim from banking system i to counterparty j. Otherwise, the net claims (liabilities). Thus, $\sum_j (x_{ij} - x_{ji})^+$ denotes the sum of positive entries and shows the bilateral netted relationship between banking systems that form our financial network and correspond to the solvency network.

For the analysis of the contagion process, positive netted positions (m_{ij}^+) and zero are only used across counterparties i and j in order to examine the systemic risk of the system and contagion dynamics through the national banking network once one or multiple borrowers are considered as defaults and not able to pay off its debt. However, the banking system requires them to hold capital in their balance sheets to cover their debt. We incorporate the Tier 1 capital to construct the final version of the network as follows,

$$\Theta = \begin{pmatrix} 0 & \frac{(x_{ij}-x_{ji})^+}{C_{20}} & \dots & \dots & \dots & \frac{(x_{ij}-x_{ji})^+}{C_{N0}} \\ \frac{(x_{ij}-x_{ji})^+}{C_{10}} & 0 & \dots & \dots & \dots & \vdots \\ \vdots & \vdots & 0 & \dots & \dots & \vdots \\ \vdots & \vdots & \vdots & 0 & \dots & \vdots \\ \vdots & \vdots & \vdots & \vdots & 0 & \frac{(x_{ij}-x_{ji})^+}{C_{N0}} \\ \frac{(x_{ij}-x_{ji})^+}{C_{10}} & \vdots & \vdots & \vdots & \frac{(x_{ij}-x_{ji})^+}{C_{j0}} & 0 \end{pmatrix} \tag{2.3}$$

The matrix Θ, known as stability matrix, represents the positive entries for net debt from FI i to counterparty j relative to denominator C_j, Tier 1 capital of country j, that is adjusted proportionately for foreign exposure. Matrix Θ is used to analyze the systemic risk and the contagion process in the next subsection.

2.3.2 Contagion and Network Stability Analysis

The analysis of the contagion process in the stability matrix is based on Furfine (2003) framework which is followed later on by Degryse et al. (2010) and Markose (2012), where the

spread of contagion is triggered by a failure of an entry in the stability matrix Θ and then propagates through the financial network. This implies that a banking system i at time 0 is triggered by the solvency of its counterparty j once the net losses from i to j that is adjusted by capital of j exceed the cure rate of capital, ρ_i. This also can be shown mathematically as follows;

$$\frac{(x_{ij} - x_{ji})^+}{C_j} > \rho_i \tag{2.4}$$

where ρ_i can be considered as a buffer loss threshold. For simplicity, we consider the homogenous $\rho = 0.06$ for all banks in the countries rather than heterogeneous ρ_i.[12] If the losses of a banking system from a failure of debt are more than the cure rate ρ, the bank's failure proceeds to the second round of contagion. The second round of contagion then happens if there are banks that have not failed in the first round and the net losses are greater than the cure rate of its capital.

Markose (2013) and Markose et al. (2021) represent a dynamic characterization of a network and the rate of contagion process through the network by applying the weighted graph and using the insight of May (1972, 2019) that system dynamics and the structure of network have a significant role in the stability of a system. The transmission of contagion is characterized on the basis of eigen-pair model in epidemiology, where cure rate and infection rate are two conditions that determine the stability of the network; The cure rate denotes a threshold of equity capital and acts as a buffer against contagion loss, and the infection rate captures the exposure of each FI's default risk to their counterparties. In this regard, the dynamics of the contagion from the failure of a banking system can be written as,

[12] The selection of a homogeneous capital loss thresholds of 0.06 was specifically based on established regulatory guidelines and standards governing distress levels and capital adequacy requirements. This value is in line with the Basel III framework's Capital Adequacy Ratio (CAR), which is directly tied to the relationship between Tier 1 capital and Risk-Weighted Assets (RWA). Basel III stipulates a minimum capital ratio of 6% concerning risk-weighted assets, indicating that the Tier 1 Capital must surpass 6% of the RWA. This benchmark is typically set by regulatory bodies and signifies the portion of initial capital allocated to mitigate potential losses.

$$
\begin{aligned}
u_{it+1} &= (1-\rho)u_{it} + \sum_j \frac{(x_{ij}-x_{ji})^+}{C_{i0}} u_{jt} \\
u_{it+1} &= (1-\rho)(1-\frac{C_{it}}{C_{i0}}) + \sum_j \frac{(x_{ij}-x_{ji})^+}{C_{i0}} u_{jt}
\end{aligned}
\tag{2.5}
$$

where u_{it+1} represents the possible default rate of banking system i at time $t+1$ which can arise from two sources; the first one captures the capital insufficiency of bank (node) i in the network, where ρ is the cure rate of capital, and thus $(1-\rho)$ can be defined as the ratio of instability due to the insufficient capital (Chakrabarti et al., 2008). Further, u_{it} reflects the rate of cumulative loss of capital for banking system i which is suffered at the time t and can be defined as $(1-\frac{C_{it}}{C_{i0}})\ \ \forall t>0$. Here, C_{it} shows the remaining resources of a bank (i.e., capital) at time t, and C_{i0} is the initial capital. Hence, the component $(1-\rho)u_{it}$ represents the rate of a bank to which the counterparty i is able to mitigate its default risk using the cure rate ρ. This implies that a banking system can protect itself from solvency by the cure rate of its capital as a buffer against losses as long as the constraint $u_{it} < \rho$ holds, meaning that acceptable losses for bank i at any time t should not exceed the rate of initial capital, ρ.

The second channel of instability can arise from the interconnection between banking systems in the network and is defined by $\sum_j \frac{(x_{ij}-x_{ji})^+}{C_{i0}} u_{jt}$. This term captures the weighted sum of the heterogeneous ratio of being suffered at time t, which stems from the bilateral net of exposures of FI i to those of counterparty j, adjusted by the capital for FI i. u_{jt} here is the representative of weights for the individual rate of default in bank counterparty j. The dynamics of the contagion process also can be shown in matrix notation as follows:

$$
U_{t+1} = \underbrace{[\Theta' + (1-\rho)I]}_{\mathrm{Q}}\ U_t \tag{2.6}
$$

where U_t is a vector of element u_{it} for $i = 1, ..., N$, and shows the potential default rate in the banking network. Θ' denotes the transpose of matrix Θ with each element $\theta'_{ij} = \theta_{ij}$, and $(1-\rho_i)I$ indicates the $N \times N$ diagonal matrix with elements $(1-\rho)$. The system stability in

Equation 2.5 and 2.6 can be examined on the basis of power iteration of the matrix Q. The model 2.6 then can yield the following form;

$$\begin{aligned} U_t &= [\Theta^{'} + (1-\rho)I]^t \; U_0 = Q^t \; U_0 \\ U_t &= Q^t \; U_0 \end{aligned} \tag{2.7}$$

According to Markose (2012) and Markose et al. (2021), the banking system network can be considered "stable" as long as $t \to \infty$ and the maximum eigenvalue of matrix Q does not exceed the threshold 1,

$$\lambda_{max}(Q) < 1 \tag{2.8}$$

This condition can also be viewed as a tipping point for the stability of the system and is compatible with reproductive (R) number in epidemiology (Van den Driessche, 2017). If the condition is not satisfied and $\lambda_{max}(Q) > 1$, the system is unstable and any exogenous shock can propagate through the whole system under no external intervention.

The advantage of the network measure maximum eigenvalue is that the maximum eigenvalue of matrix Θ and its associated right and left eigenvector still contain more information to use concerning the systemic importance and systemic vulnerability of individual banking systems in the network. Eigenvector centrality is a network centrality that is used by Markose et al. (2012) and shows the best correlation with capturing of a node to propagate the largest contagion process (losses) on others deriving from stress test in the Furfine (2003). Eigenvector centrality is obtained for the netted matrix Θ and characterizes the degree of concentration of activity for each node, and thereby is strictly concerned with the stability of the network.

$$\tilde{\nu}_i = \frac{1}{\lambda_{max}(\Theta')} \sum_j \theta_{ij} \tilde{\nu}_j \tag{2.9}$$

where $\tilde{\nu}_i$ denotes the right eigenvector centrality for an individual bank i and as can be seen in Equation 2.9, the centrality score of bank i is associated with the centrality score of all other connected banks $\tilde{\nu}_j$ in the network, weighted by the net liabilities to Tier 1 capital ratio. The eigenvector equation of matrix Θ can be rearranged and written for the eigen-pair $(\lambda_{max}(\Theta^{'}), \tilde{\nu})$ by vector notation,

$$\Theta\tilde{\nu} = \lambda_{max}(\Theta^{'})\tilde{\nu} \tag{2.10}$$

where $\tilde{\nu}$ is the right eigenvector of the stability matrix in Equation 2.9 and identifies the systemic important banking systems. This implies that banking systems with high eigenvector centrality are connected with many highly interconnected counterparties so they potentially can contribute relatively more to the instability of the financial network if $\lambda_{max}(\Theta^{'}) > \rho$ (Heath et al., 2016). The banking system with the high right eigenvector can be considered the banks with the highest amount of net liabilities in the system (i.e., the main borrowers). Additionally, since the maximum eigenvalue of a matrix and its transpose are the same, then the left eigenvector of the matrix Θ using Equation 2.10 can be also expressed as,

$$\Theta^{'}v = \lambda_{max}(\Theta^{'})v \tag{2.11}$$

where v is the left eigenvector and can reflect the vulnerability index since it captures the effect of the exposures of each bank to other banks. This can be associated with the banking systems with the highest amount of claims in the system (i.e., the main lenders).

2.4 Data

The starting point to examine the question of how the solvency of a FI affects the stability of our financial network is to build a bilateral matrix X for the Core Global Banking Systems(CGBS)

explained in Section 2.3. The CGBS relies on *BIS Consolidated Banking Statistics (BCBS)*, which is published by the Bank of International Settlements (BIS) organization.[13] The BCBS provides the balance sheet data on cross-border banking systems that reflect the exposure of active banks of different countries based on an ultimate risk at an international level. The ultimate risk captures the credit risk mitigants (such as guarantees, collateral, etc.) that transmit the credit exposure of a bank from a counterparty to another one. The details in the BCBS shed light on the worldwide consolidated positions of top active banking groups in reporting countries. The data provides the claims (liabilities) of banks' foreign affiliates at the aggregate level of the banking system without considering intragroup positions, rather than an individual bank level. In this paper, the data of BIS Consolidated Banking Statistics is included *19 reporting national banking systems* from 2005:Q1 to 2020:Q1.[14]

Figure A.4 in Appendix A.4 shows the total gross foreign claims (receivables) for each banking system j, which is the sum over row i in matrix X and associated with the asset side of the balance sheet. As shown in Figure A.4, France, the UK, the US, Germany, and Japan generally are the banking systems with the highest total gross foreign claims during the sample period. However, on the liability side, Figure A.5 represents the total gross foreign liabilities (payables) for each banking system i that is the sum over j columns or counterparties. Figure A.5 shows that the US, UK, France, Germany, and Japan are respectively top banking systems in terms of total gross foreign liabilities. The total gross foreign claims and liabilities are concerned with Equations 2.2 in Section 2.3.

The next step is to adjust the netted position by *Tier 1 capital* which captures the losses transferring from the banks. The size and the dynamics of the banking system's capital are crucial to the analysis of the vulnerability of the system since they are directly associated with

[13]The BIS statistics can be found in Table 4 in https://www.bis.org.

[14]In this study, the reporting countries have been classified into four different categories based on connectivity: Core economies, European non-GIIPS economies, GIIPS countries, and others. The *core economies* are the United States, United Kingdom, Japan, and Switzerland. The *EU non-GIIPS economies* include Austria, Belgium, Finland, France, Germany, and the Netherlands. The *GIIPS countries* refer to Greece, Italy, Ireland, Portugal, and Spain, which were affected severely after the outbreak of the GFC and during the Eurozone crisis. The *others* are considered Australia, Canada, Sweden, and Turkey.

the ability of the banking system to absorb shocks. The Tier 1 capital is taken from the IMF database, which reports the data quarterly for every bank separately.[15] Figure A.1 in Appendix A.3 plots the time series of Tier 1 capital in billion dollars from 2005:Q1 to 2020:Q1 for all BIS reporting banking systems based on their sovereign. As it can be seen, the regulatory Tier 1 capital for the total consolidated banking statistics generally has upward trends during the whole sample period (see Figure A.2 in Appendix).

It is important to note that the total Tier 1 capital does not represent the Tier 1 capital for the cross-border banking system. In order to obtain the Tier 1 capital of the cross-border banking system which is based on the consolidated banking system, the total Tier 1 capital is required to scale down only to the liabilities of the banking system in BIS statistics.[16] For example, the total Tier 1 capital for the US banking system is \$1,112 billion, but only %14 of banking system claims on all sectors cover the cross-border flows, which is about \$158 billion.[17] The time series of *adjusted Tier 1 capital* in Figure 2.1 is given for our sample period in order to illustrate only the cross-border banking system.

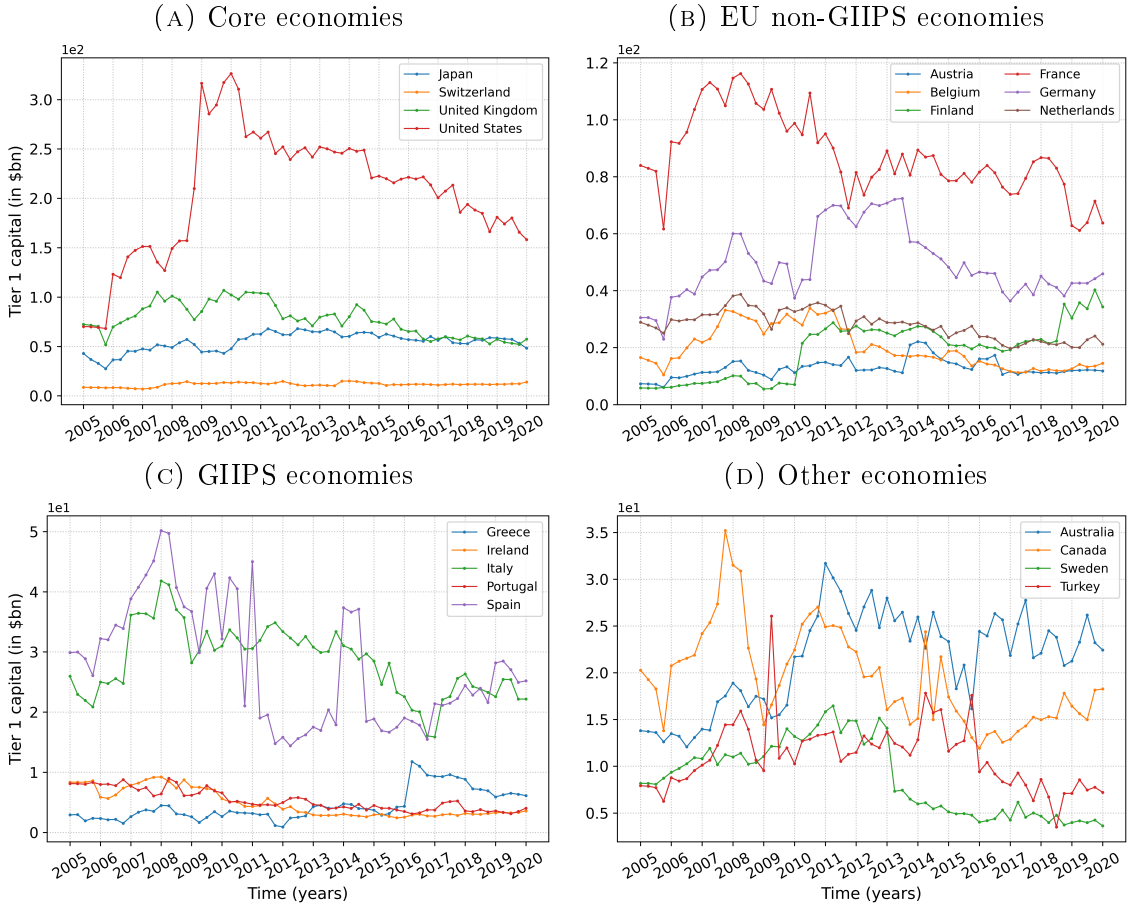
Figure 2.1 plots the adjusted Tier 1 capital for all the cross-border banking systems in four categories. The top five banking systems with the highest Tier 1 capital are the US, France, UK, Japan, and Germany with an average of about 215, 87, 77, 56, and 50 billion dollars, respectively. Most of the core economies and EU economies (including GIIPS economies) keep their Tier 1 capital at almost a constant level during our sample period. Unlike other countries in these groups, the US, Italy, France, and Spain decrease significantly their regulatory capital in their banking systems, especially after the GFC crisis. The main reason for such a decline can be explained by reducing the size of claims in their consolidated banking systems within this period (see Figure A.4 in Appendix).

[15] The IMF data can be found in https://data.imf.org.

[16] Here, the total amount of Tier 1 capital for cross-border reporting banking system is adjusted by the adjustment ratio $\frac{\sum_{b^R} \sum_{j \neq i} X^F_{B_j {}^{b^R}_{i}}}{\sum_{b^R} \sum_{j \neq i} X^F_{S_j {}^{b^R}_{i}}}$.

[17] More details are explained in Annex A.1, A.2, and A.3 in Appendix.

FIGURE 2.1: Adjusted Tier 1 capital time series of BIS reporting banks

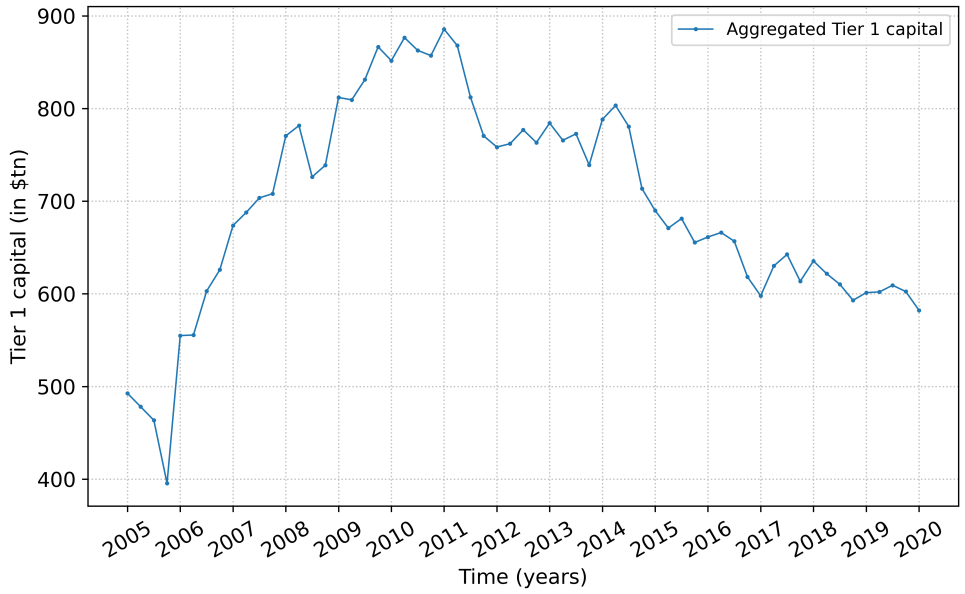


Note: Figure exhibits quarterly adjusted Tier 1 capital in billion US dollars for BIS reporting Banking systems between 2005:Q1 and 2020:Q1. The top five banking systems with the highest Tier 1 capital are the US, France, UK, Japan, and Germany with an average of about 215, 87, 77, 56, and 50 billion dollars, respectively. Here, "e" means exponent and 1e1 and 1e2 are the scientific notation which means 10 to the power of 1 and 2, respectively.

Data source: Calculated and plotted by the author using IMF database.

Additionally, Figure 2.2 plots the aggregated adjusted Tier 1 capital time series to show the general trend of Tier 1 capital holding in the consolidated banks rather than the total amount of regulatory capital. As explained before, the adjusted Tier 1 capital is necessary to address the cross-border reporting banking system exposure to the liabilities of other banks (see Annex A.2 in Appendix). Figure 2.2 represents the significant growth of Tier 1 capital in the consolidated banks up to about $900 trillion in 2011:Q1 and then started decreasing to the lowest level in post-GFC at around $600 trillion in 2020:Q1.

FIGURE 2.2: Aggregated adjusted Tier 1 capital time series of 19 BIS reporting banks



Note: Figure exhibits the aggregated adjusted Tier 1 capital time series in trillion dollars from 2005:Q1 to 2020:Q1 for the BIS reporting countries.
Data source: Calculated and plotted by the author using IMF database.

2.5 Empirical Results

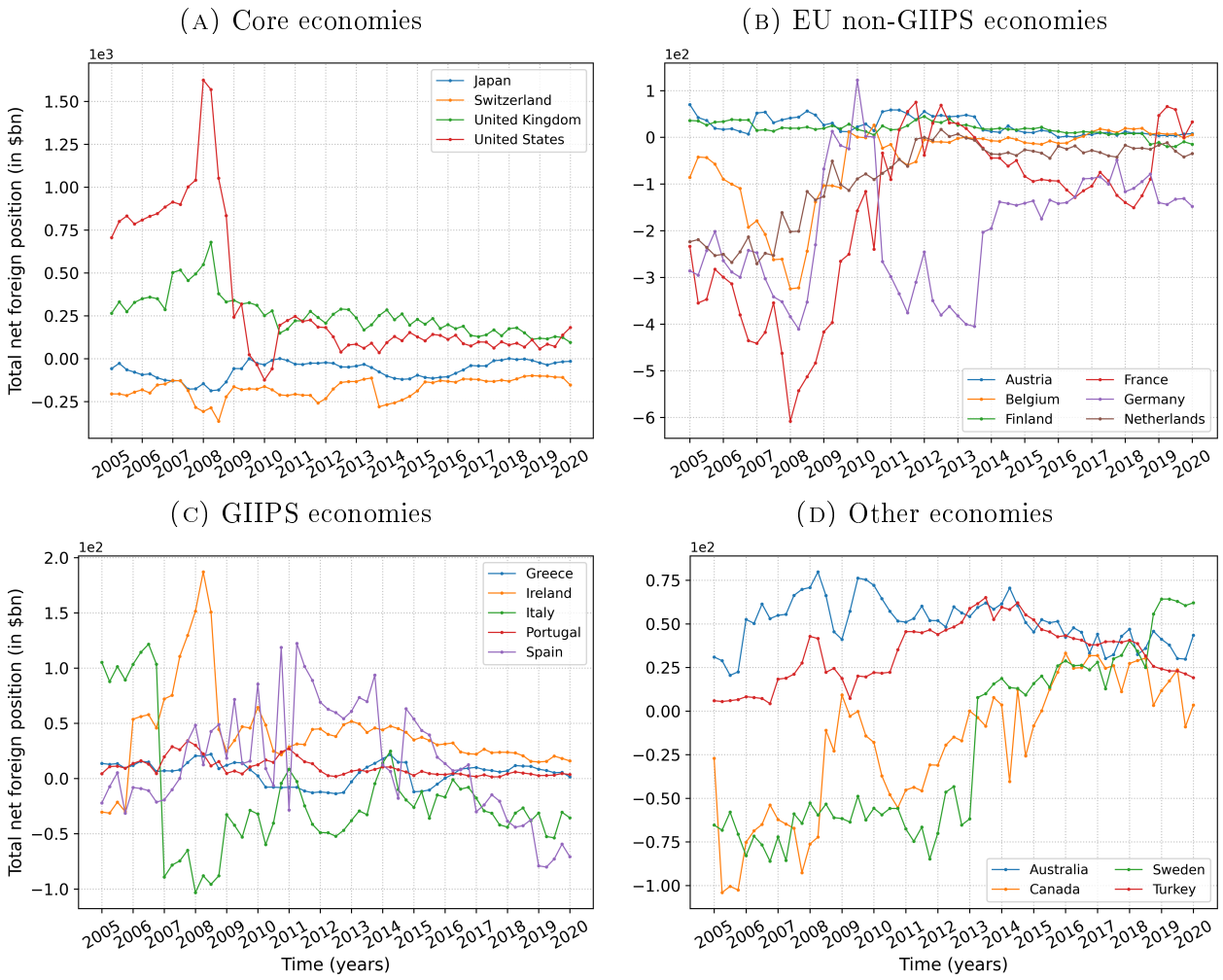
This section first analyses the cross-border data for the BIS reporting banking systems within the period 2005:Q1 and 2020:Q1. The second part focuses more on the cross-border banking networks. Finally, we analyze the propagation of contagion within the financial network to study how the risk of a bank's default can spread through the whole network.

2.5.1 Country Cross-border Analysis

We start the cross-border banking analysis with the net liabilities consolidated banking system as the systemic risk is strictly associated with the net liability position in matrix M (i.e., the numerator of entries in the stability matrix Θ) in Section 2.3. Figure 2.3 plots the net liabilities positions for the BIS reporting banking system for the period between 2005:Q1

to 2020:Q1. As can be observed in Figure 2.3, the top countries with the highest net liabilities (i.e., net borrowers or debtors) are the US, UK, Australia, Ireland, and Turkey with on average about 320, 256, 52, 44, and 34 billion dollars. The top countries with the highest net claims (i.e., net lenders) are Germany, Switzerland, France, Netherlands, and Japan with an average of around 196, 174, 157, 79, and 65 billion dollars. Another feature that can be seen is the position of Turkey, the increase in the liabilities of the Turkish banking system since 2010 is along with the accelerating loss of value in Turkish currency (Turkish lira) relative to other currencies such as the Euro and USD, which lead to the outflow of capital.

FIGURE 2.3: Total net foreign liabilities of BIS reporting banks

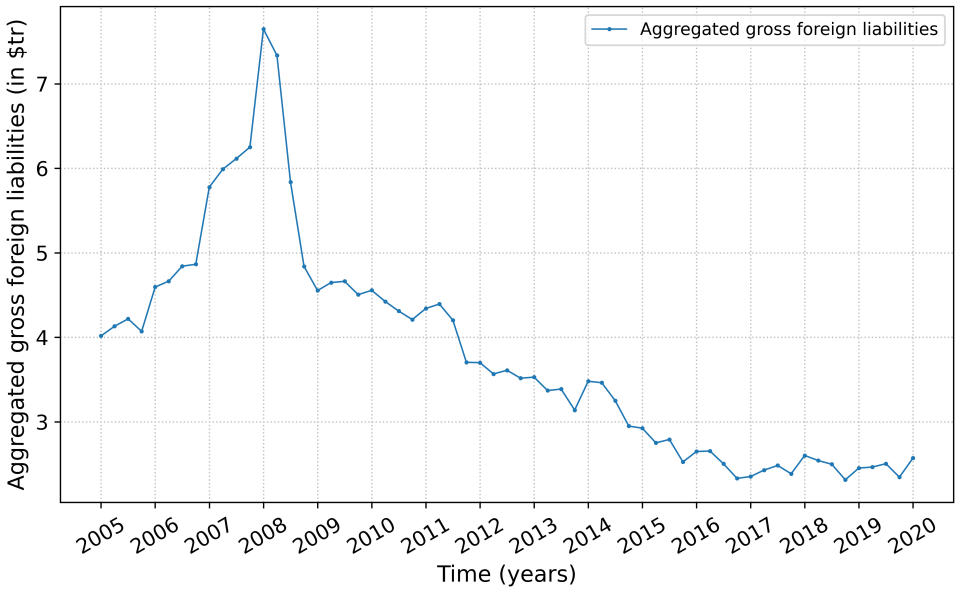


Note: The Figure shows the total net foreign liabilities in million dollars for the BIS reporting countries from 2005:Q1 to 2020:Q1. The top countries with the highest liabilities are the US, UK, Australia, Ireland, and Turkey with on average about 320, 256, 52, 44, and 34 billion dollars. The top countries with the highest claims are Germany, Switzerland, France, Netherlands, and Japan with on average around 196, 174, 157, 79, and 65 billion dollars.

Data source: BIS consolidated banking system statistics.

The total gross claims for all the banking groups in Figure 2.4 can be informative since it is strictly concerned with the dynamics of the systemic risk index and it may be subject to losses as a consequence of the solvency. Figure 2.4 shows a decreasing trend overall over our sample period. The aggregated gross liabilities increased and peaked at about 8 trillion dollars during the 2008 financial crisis, and it started decreasing in post-GFC to the lowest point at around $1.5 trillion.

FIGURE 2.4: Aggregated gross foreign liabilities of 19 BIS reporting banks

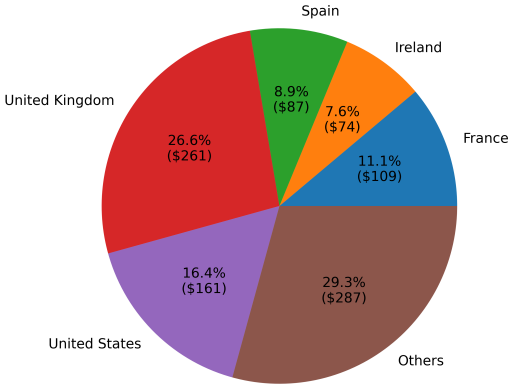


Note: The Figure exhibits gross foreign liabilities in trillion dollars for the BIS reporting countries from 2005:Q1 to 2020:Q1.
Data source: BIS consolidated banking system statistics.

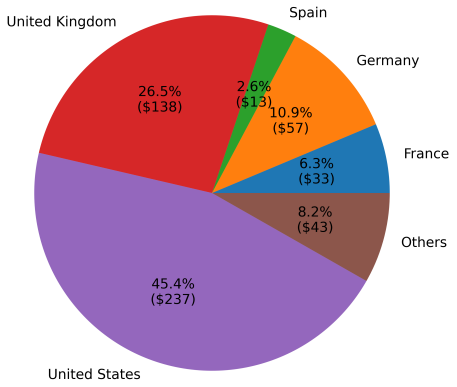
Figure 2.5 then shows the cross-border claims of main lenders - Germany, Switzerland, France, Netherlands, and Japan - on their main borrowers. As it can be observed, the US and UK are the sovereigns with the most liabilities as the joint liabilities of these two banking systems on Japan, France, Germany, Switzerland, and Spain are 50%, 42.4%, 37%, 63.7%, and 29.6%, respectively. This implies the critical roles of the US and UK in the cross-border banking system and warns about the devastating consequence of failing these two countries and approving the works by Furfine (2003) and Degryse et al. (2010). This also shows the main role of these countries in international banking flows among advanced economies which is in line with earlier work Milesi-Ferretti and Tille (2011) and Hoggarth et al. (2010).

FIGURE 2.5: Cross-border banking systems exposures of the top lenders

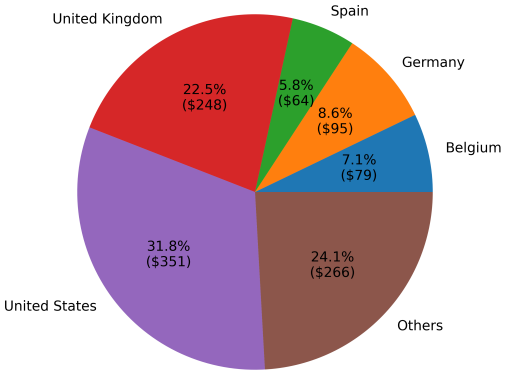
(A) Claims of Germany



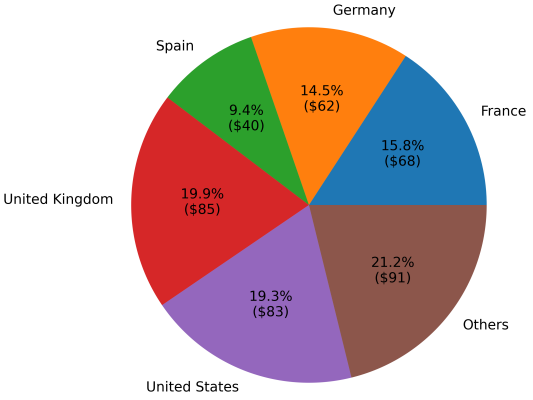
(B) Claims of Switzerland



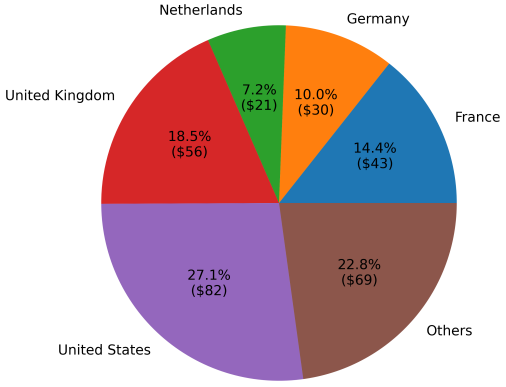
(C) Claims of France



(D) Claims of Netherlands



(E) Claims of Japan



Note: The Figure plots cross-border banking systems exposures of the main 5 lenders - Germany, Switzerland, France, Netherlands, and Japan - to their main borrowers during the sample period. The figures in parentheses report the amounts of claims in billion dollars for the associated banking system.

Data source: BIS consolidated banking system statistics.

Figure A.6 in Appendix A.6 also represent the top 5 borrowers - the US, UK, Germany, Netherlands, and Spain - with their main lenders between 2005:Q1 and 2020:Q1. It appears that Germany, UK, Japan, Switzerland, and France are the banking system that is mainly exposed to them. For instance, the joint claims of these banking systems in the US, UK, Germany, Netherlands, and Spain are 53.4, 58.4, 83.6, 96.2, and 85.3 percent of the total claims of 19 reporting BIS banking systems, respectively. It can be observed that all of the debt of the top main borrowers is held by almost the core and developed (plus Spain) economies.

2.5.2 Cross-border Network Analysis

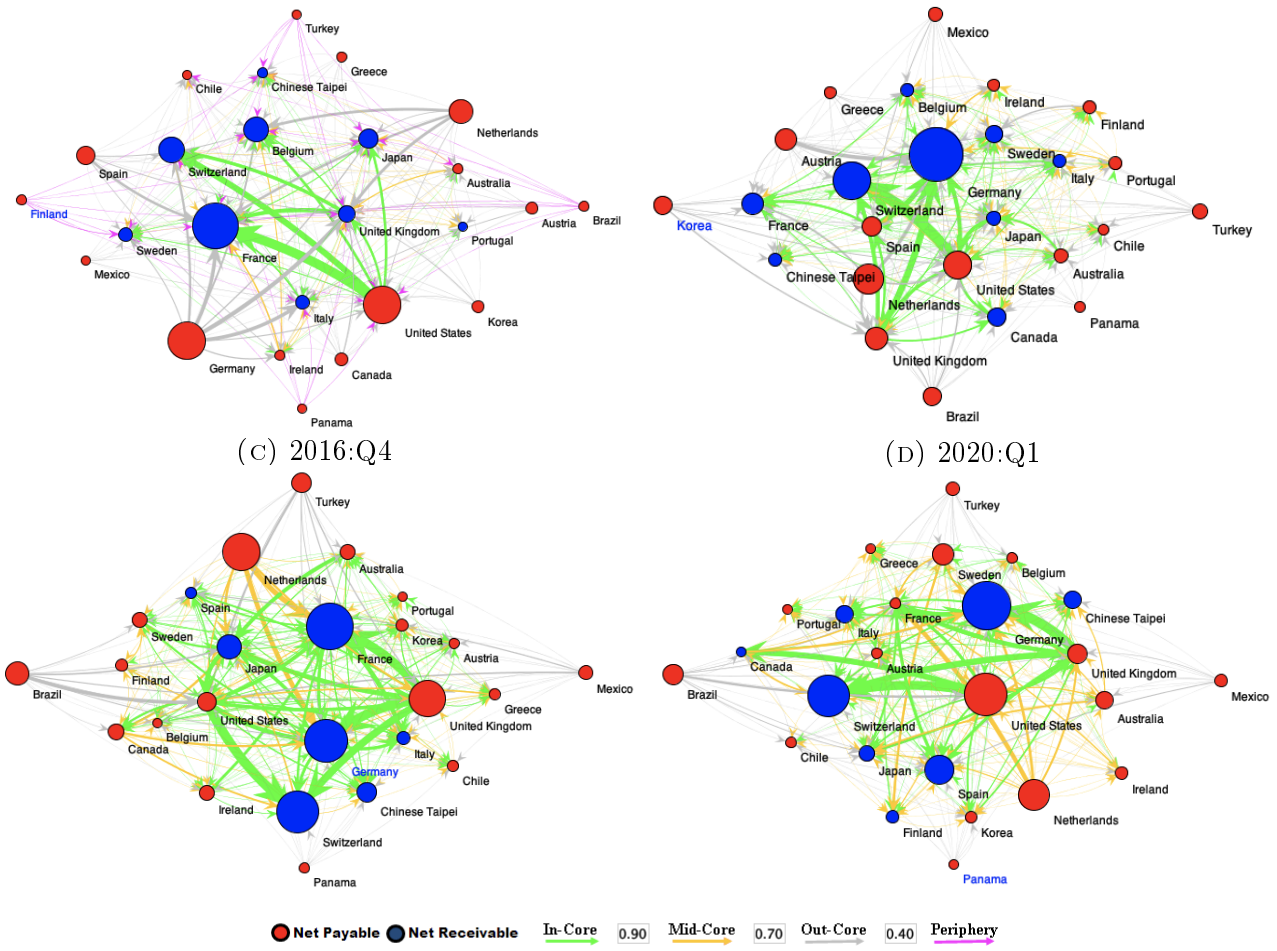
After conducting the preliminary analysis of the cross-border banking system, with a focus solely on the balance sheet data in isolation and without incorporating any network or relational considerations, we now present the network interactions between countries in Figure 2.6. The figure is associated with the network Θ in Section 2.3 and visualizes the exposure of cross-border banking systems to characterize the dynamic of financial networks for four different periods 2007:Q4 (pre-GFC), 2010:Q4 (mid-European debt crisis), 2016:Q4 (post-crises), and 2020:Q1.

Figure 2.6 evaluates the comprehensive connectivity across all banking systems to create the tiered layout. This evaluation involved calculating the ratio of total in- and out-degrees for each banking system in relation to the total connections of the most connected bank. The resulting ratios served as normalized measures of connectivity. The network is then categorized into distinct tiers based on these ratios. Banks exhibiting ratios within the top 10% (90th percentile) formed the network's inner core, representing the most highly connected entities. Those with ratios ranging from the 70th to the 90th percentile constituted the mid-core, displaying substantial connectivity. A subsequent tier, known as the out-core, encompassed banks with ratios between the 40th and 70th percentiles, signifying a moderate level of connectivity. Finally, banks falling below the 40th percentile in terms of ratios were classified as the periphery,

highlighting their position at the outer edges of the network. This tiered approach effectively visualizes the varying degrees of connectivity and centrality within the cross-border banking network.

The red and the blue nodes represent respectively the net borrower (net payable) and the net lender (net receivable) countries. The size of the nodes denotes the weight of every banking system, and the arrows show the relationship between countries. In Figure 2.6 countries such as US and UK are the main net borrowers among the reporting banking systems, and countries primarily raised funds from Japan, Canada, Switzerland, Spain, Germany, and France, which are the main net lenders.

FIGURE 2.6: Network visualization for the cross-border bilateral exposures



Note: The Figure shows network visualization for cross-border bilateral exposures for BIS reporting countries. The red nodes are the net payables (borrowers), the blue nodes are the net receivables (lenders), and the arrows denote the relationships between banking systems. Data source: BIS consolidated banking system statistics.[18]

Figure 2.6 also can be shown numerically by network statistics in Table A.1 in Appendix A.7 for the whole sample. Table A.1 reflects the characterization of financial networks from 2005:Q1 to 2020:Q1. The number of nodes which is 19 can be referred to as the size of our network. As can be observed, edges have gradually increased from 193 in 2005:Q1 to 264 in 2020:Q1. This can imply that the financial network is far away from the complete network as the number of edges for the complete directed graph is computed by $N(N-1)$ which is 600.

[18]The Figure plotted using the network simulator developed by Dr. Simone Giansante.

There are other simplest network metrics are in- and out- degrees which show the linkages between nodes. In-degrees are the edges that end at a node, and out-degrees are the ones that originate from a node. In the financial terminology of networks in-degrees and out-degrees of nodes are interpreted respectively as lending to and borrowing from an agent. Table A.1 shows that in- and out- degree grow on average, which can represent the growing number of borrower and lender countries between 2005:Q1 and 2020:Q1. This trend can confirm the increasing number of contractual links between banking systems during the sample period.

The mean of a node is another measure that refers to the average number of edges connected to it. That is, in the case of a directed graph follows as $k = \frac{E}{N}$. In a directed graph, the number of edges (m) is equal to the number of in-degree (incoming) edges or equivalently to the total number of out-degree (outgoing) edges so $m = \sum_{i=1} a_i^{in} = \sum_{j=1} a_j^{out}$. Thus, as it can be observed in Table A.1 (or Figure 2.7a), mean in-degree and out-degree increased from 7.72 in 2006:Q1 to 10.56 in 2020:Q1. Note that the mean in-degree and the mean out-degree for every period are equal since $mean_i^{out} = \frac{1}{n}\sum_{j=1} a_i^{out} = \frac{1}{n}\sum_{i=1} a_j^{in} = mean_j^{in}$. According to 2.7(b), the in-degree distribution is less uniform than the out-degree distribution. The standard deviation is around 7.5 at the beginning of the period and decrease to less than 6.5 in 2020:Q1. However, the standard deviation is about 5 during the whole period although there are some fluctuations, especially between 2011 and 2013.

The degree distribution is highly skewed (asymmetric) in most real networks. As can be observed in 2.7(c), the degree distribution of the cross-border banking system network displays notable asymmetry throughout the entire sample period, indicating an inherent imbalance within the international banking landscape. Specifically, the distribution highlights that a substantial proportion of nodes (in this context, referring to banking systems) exhibit low degrees of connectivity, which corresponds to a limited extent of liabilities. In contrast, a small yet significant number of banks display remarkably high degrees of connectivity, suggesting a concentrated group of nodes with extensive liabilities. This phenomenon points to the presence of hub nodes, which can be defined as highly connected entities within the global banking

system. The banking system hub plays a pivotal role in shaping the network's structure and dynamics, reflecting their central significance in cross-border financial interactions. The hub is also associated with the in-core in Figure 2.6.

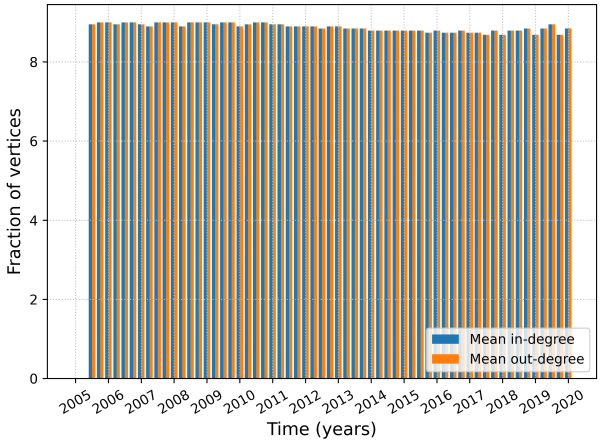
Regarding the in- and out-skewness, they have diverging behavior from the beginning of the period until 2011. Skew in-degree is positive during 2005 and 2011, which shows the right skewness for the borrowing data. That is, the high amounts of funds points have higher values. While, out-degree skewness mostly is negative and starts at a rate of -0.38 in 2005:Q1, and grows to about -0.25 in 2020:Q1, which implies the pressure of borrowing decreases during the whole period. That can be explained by bailing out of companies and banking systems by government resources (such as Federal Reserve and Bank of England) in order to support them and prevent financial contagion to other parts of the economy between 2008:Q4 and 2014:Q4 (Moosa, 2010; Tucker, 2018). The measure shows an increase in pressure of borrowing by unwinding the monetary policy from 2015:Q2, reflecting that the economy could recover itself from the crisis. Kurtosis is also a measure to characterize variability and indicate whether the data are light-tailed or heavy-tailed compared to a normal distribution. Figure 2.7(d) shows that the financial network generally is a distribution with a negative kurtosis value, which indicates the global banking system's distribution has a lighter tail compared to the Gaussian distribution. The implication is that the majority of funding is generally financed near the mean and a small number of funding is located on the tails. The kurtosis out-degree is relatively more light-tailed than the in-degree distribution.

A low clustering coefficient throughout the period corresponds to low local interconnectedness and banking systems that do not function as hubs in the core. The observed clustering coefficients in Table A.1 are in the range of 0.41 to 0.46 compared to an Erdos-Renyi random graph which is about 1%. This provides insights into the structural dynamics of the analyzed network, indicating that the banks within the network exhibit a remarkable tendency to form clusters or tightly interconnected groups or communities. This deviation from randomness signifies that the network's connectivity patterns are not a result of random connections but

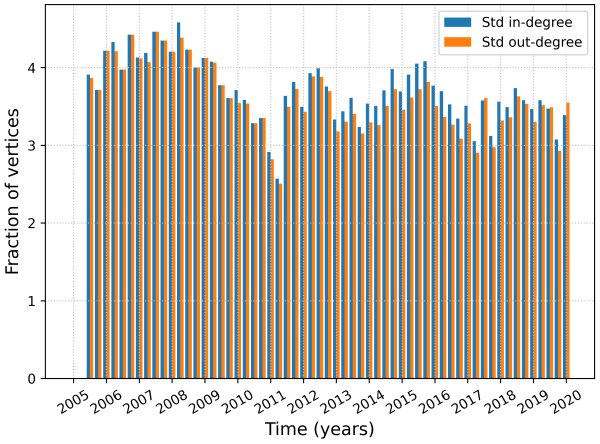
rather reflect deliberate and meaningful interactions. The higher clustering coefficients implies the existence of key banking system or in-core banks that facilitate communication and connections between various clusters (see more details in Appendix A.5 for the defintion of connectivity and clustering coefficient).

FIGURE 2.7: Statistical network analysis

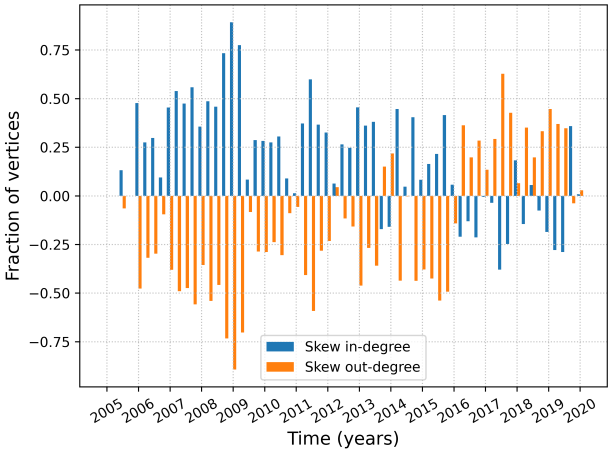
(A) Mean



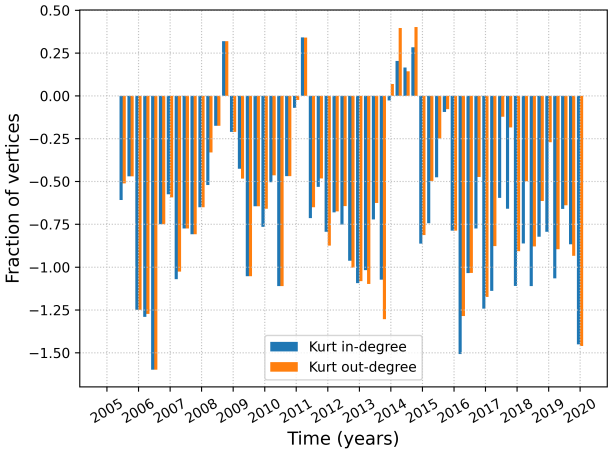
(B) Standard deviation



(C) Skewness



(D) Kurtosis

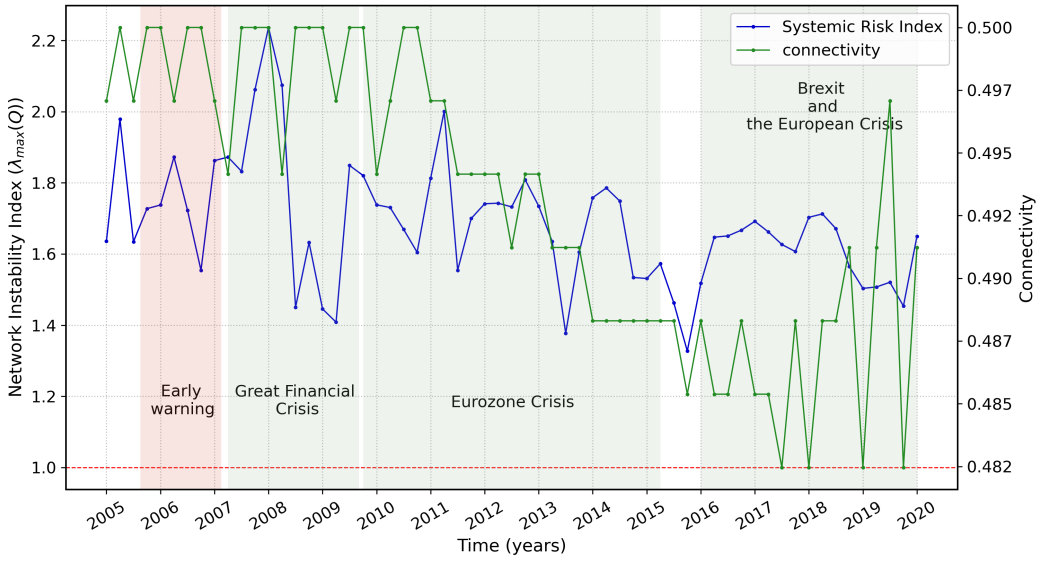


Note: The Figures plot network statistics - mean, standard deviation, skewness, and kurtosis - from 2005:Q1 to 2020:Q1 for the BIS reporting banking systems.
Data source: BIS consolidated banking system statistics.

So far, we have shown how the national banking systems interact in the international banking system network and how in a real-world network, a cross-border banking system tends to form clusters and make the system imbalanced. In such a system, a measure that reflects the instability of the system based on the interaction of its components is needed. We use the

framework in Section 2.3 and discuss the stability of the cross-border banking system using Figure 2.8. The figure plots the maximum eigenvalue of matrix Q that indicates the Systemic Risk Index (SRI) and reflects the instability of the system (i.e., cross-border banking system) (Markose et al., 2021). Since the SRI captures the interconnectedness between FIs and capital inadequacy, we found it desirable to plot the connectivity metric to show the role of connectivity of the banking systems in the dynamic of the SRI. The connectivity metric also implies the likelihood of a connection between two banking systems by flows of claims (See more details in Appendix A.5). Figure 2.8 illustrates a positive correlation between connectivity and stability of the network with the correlation coefficient of 0.52, which is a moderate positive relationship and indicates how connectivity can play role in a forming the systemic risk in the cross-border banking system.

FIGURE 2.8: Connectivity and network instability index



Note: The Figure shows the relationship between the connectivity and network instability index from 2005:Q1 to 2020:Q1 for the BIS reporting countries. The left axis represents the network instability index, and the right axis shows the connectivity.
Source: Calculated and plotted by the author using BIS and IMF databases.

The maximum eigenvalue of matrix Q in Figure 2.8 can show the instability of the cross-border banking network and is consistent with the financial crisis during the sample period of 2005 to 2020. The $\lambda_{max}(Q)$ is always more than the stability threshold of 1, which is a high

value reflecting the existence of high systemic risk and unstable global banking system during 2005:Q1 and 2020:Q1. Before the 2007-8 financial crisis, the index was relatively at the highest which can be considered as a warning in the pre-GFC crisis about the instability of the global banking network. The index then shows the highest risk with a peak at about 2.2 in 2008:Q1 just before the collapse of Lehman Brothers in 2008:Q3. The spectral SRI starts decreasing to the lowest point at 1.4 in the post-GFC in 2009:Q1. The λ_{max} increases with the Eurozone sovereign debt crisis with a jump to about 1.85 in 2009:Q2, just before the financial crisis hit Europe in 2009:Q4 when Greece announced its unexpected budget deficits and accelerating debts for the first time. It was a consequence of the Great Recession when the banking system had experienced huge capital losses, and most European countries bailed out some banks with several supporting recapitalization loans due to the strong interconnections (Copelovitch et al., 2016; Frieden and Walter, 2017). The $\lambda_{max}(Q)$ stays in a high value until the end of the Eurozone crisis. The spectral SRI decreases to the lowest value of about 1.3 from 2005:Q2 to 2016:Q1 when there is no crisis in the global financial system. However, the eigenvalue started increasing In early 2016, corresponding to the UK voting to leave the European Union (i.e., BREXIT) and fueling concerns across the continent in the financial market. Thus, investors fled to safety assets and pushed yields to negative values (Bien et al., 2019). Also, In mid-2016, 17% of loans ($400 billion) in Italian banks shrank, and banks required a bailout.

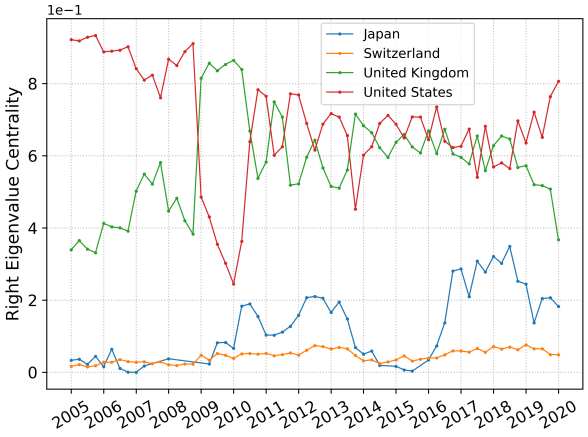
Regarding the connectivity, as can be supported in Figure 2.8, ranges of connectivity during the whole period are (0.482,0.497) which is a relatively moderate level of connectivity. The connectivity is at its highest with around 0.498 degrees of interconnectivity before the 2007-8 crisis, but, with the collapse of two Bear Stearns hedge funds in 2007:Q2, it dropped to 0.494. This is aligned with Hattori et al. (2007) and Degryse et al. (2010) which show the role of growing interconnections in the financial system up to the 2007-2008 crisis. After GFC, there were a few larger fluctuations within the range of (0.494,0.50) until the end of 2011. The connectivity started decreasing during the Eurozone crisis down to the lowest degree at about 0.482 in the mid-Brexit and the European crisis in 2017:Q3. Since then until the end of the

sample period, there have been some fluctuations in the connectivity index. Analyzing the BIS banking system to banking system data reveals fluctuations attributed to the connection with Turkey, notably marked by increased liabilities on other banking systems, such as Finland and Portugal. This trend directly addresses the impact of the Turkish Lira crisis experienced in recent years.

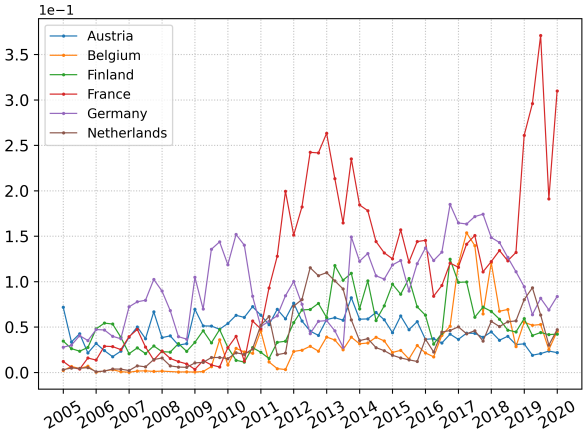
By analyzing the moments of the degree distribution earlier, we demonstrated that a small number of banks play a more significant role in the cross-border banking system and consequently contribute more to the system's instability. However, a systemic risk analysis is essential for identifying the influence of each component on the entire system. Equations 2.10 and 2.11 in Section 2.3 can address the role of each national bank by ranking them within the cross-border banking system by decomposition of the network Θ. Figure 2.9 is associated with Equations 2.10 and reports the evolution of right eigenvector centralities for each sovereign bank. Similar to the concept discussed in Markose (2012), right eigenvector centrality involves ranking the significant components within a system, and hence, a high eigenvector centrality indicates considerable systemic importance within the banking system. Referring to Figure 2.9, our findings indicate that, over the sample period, the United States and the United Kingdom hold the highest systemic importance among all countries. Our findings confirm Furfine (2003) and Degryse et al. (2010) which were some of the first warnings about the threatening role of the US and UK banking systems to the global financial market. Spain, Germany, and France follow as the third, fourth, and fifth most systemically important banking systems in the BIS reporting cross-border banking system. Note that the high right eigenvector centrality of the Turkish banking system in post-2010 can reflect the high amount of liabilities that arise from deteriorating the Turkish lira and the outflow of capital.

FIGURE 2.9: Dynamic of Systemic Importance Index of Cross-border Banking Systerms

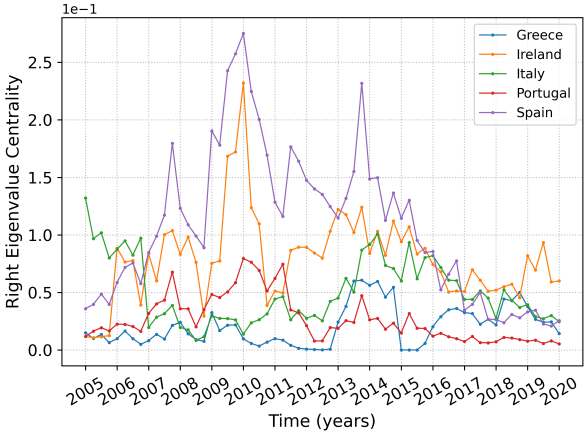
(A) Core economies



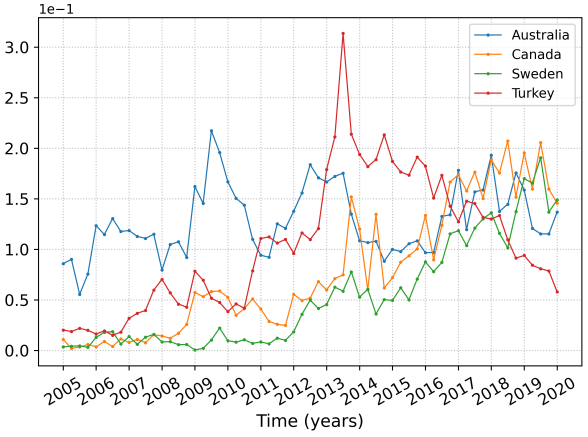
(B) EU non-GIIPS economies



(C) GIIPS economies



(D) Other economies



Note: The Figure shows systemically important banking systems based on right eigenvector centrality from 2005:Q1 to 2020:Q1. The top 5 systemic important countries are the US, UK, Spain, Germany, and France with the highest right eigenvector of 0.69, 0.58, 0.13, 0.11, and 0.11, respectively.

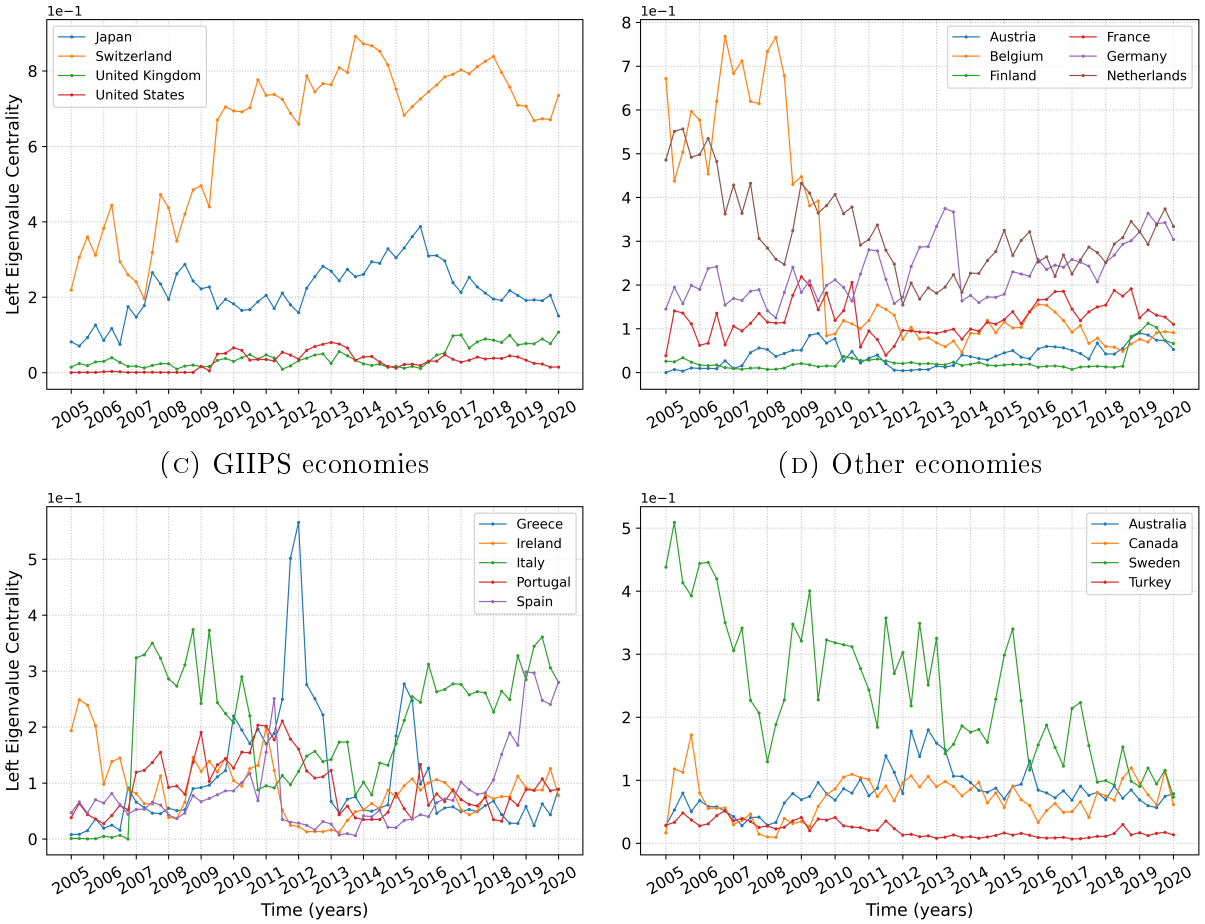
Source: Calculated and plotted by the author using BIS and IMF databases.

Additionally, Figure 2.10 is associated with Equation 2.11 and shows the vulnerability of each network's components by evaluating the evolution of left eigenvector centrality during the sample period. This indicator represents the effect of the exposures of each bank to other banking systems as Markose (2012) mentioned. As can be observed in Figure 2.10, Japan by far is the most vulnerable banking system with a left eigenvector of 0.67 on average, followed respectively by Switzerland and Italy with 0.25 and 0.24 in the whole period. Germany and Belgium are the fourth and fifth vulnerable countries with 0.21 and 0.19. Note that Spain

becomes one of the main vulnerable countries after 2016. It implies the high amount of debt that Spain holds especially after 2016. According to Figure 2.3, Spain's position changed from a net borrower to a net lender after 2015:Q2.

FIGURE 2.10: Dynamic of Systemic Vulnerability Index of Cross-border Banking Systerms

(A) Core economies (B) EU non-GIIPS economies



(C) GIIPS economies (D) Other economies

Note: The Figure plots systemically vulnerable banking systems based on left eigenvector centrality from 2005:Q1 to 2020:Q1. The top 5 systemic vulnerable countries are Japan, Switzerland, Italy, Germany, and Belgium with the highest left eigenvector of 0.67, 0.25, 0.25, 0.21, and 0.19, respectively.

Source: Calculated and plotted by the author using BIS and IMF databases.

2.5.3 Contagion Analysis

So far, the financial network's characteristics and stability of the cross-border banking system are analyzed using net liabilities and Tier 1 capital of BIS reporting countries within

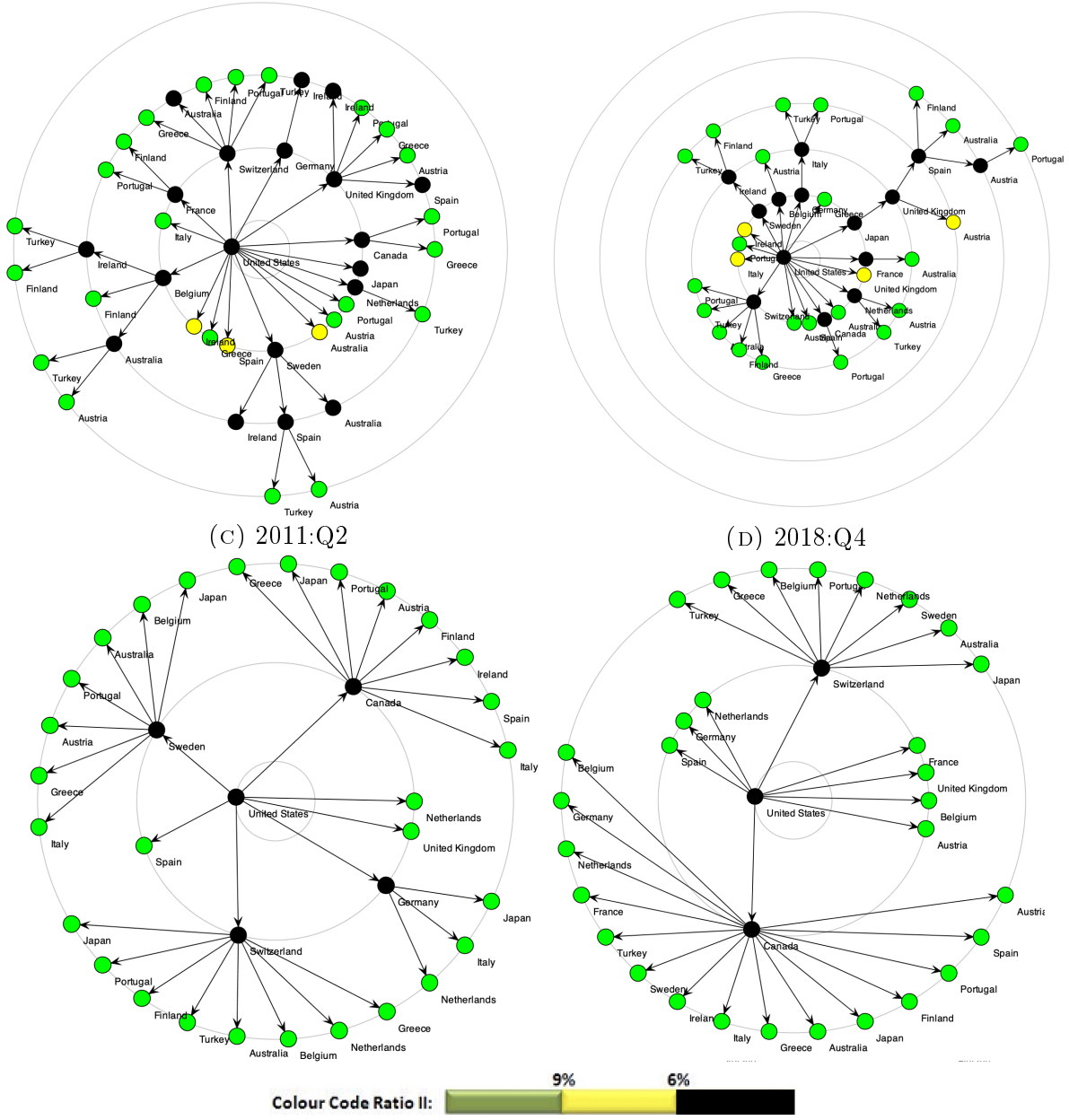
the period 2005:Q1 to 2020:Q1. We also ranked the systemically most important and vulnerable banking systems in the global banking system. In this Section, we provide the empirical results related to Equation 2.5 and show how the default risk can spread through the cross-border banking system once an exogenous shock hits a banking system. We analyze the contagion process in Table A.2 to evaluate the consequences of failing the top three systemically important banking systems from the 1st quarter of 2005 to the first quarter of 2020.

Figure 2.11 visualizes the destructive consequences of "too interconnected to fail" and "too big to fail" phenomena using the contagion process explained in Equation 2.5 (Markose et al., 2012; Strahan, 2013; Acemoglu et al., 2015). The figure shows the network of the global banking system that has a clustered central core and leads to the propagation of contagion through the network of banks. We assume a 6% capital threshold for the dynamic of the system in Equation 2.5. Further, the black nodes indicate the defaulted banking systems with $\rho < 0.06$, the yellow nodes show the national banking system with $0.06 < \rho < 0.09$, and the green nodes are banking systems with $\rho > 0.06$. According to Figure 2.11, failure of the US banking system as the most important bank can spread to the second iteration (q=2) of the tiered network if no intervention occurs (see the sample contagion process). The figure exhibits more number of failed banking systems prior to the 2008 financial crisis once the systemic risk and connectivity in Figure 2.8 are at the highest degree. As we move toward the end of the sample period 2020 and the systemic risk decreases, the number of failed banks and the rate of contagion reduces. As can be observed, in the 2008 crisis, the failure of the US spread through the system by killing 14 banks in the first round of contagion. This number decreases to 2 banking systems in 2020:Q1, i.e. Switzerland and Canada.

FIGURE 2.11: Contagion Process in Response to the US Banking System Failure

(A) 2005:Q4

(B) 2008:Q1



(C) 2011:Q2

(D) 2018:Q4

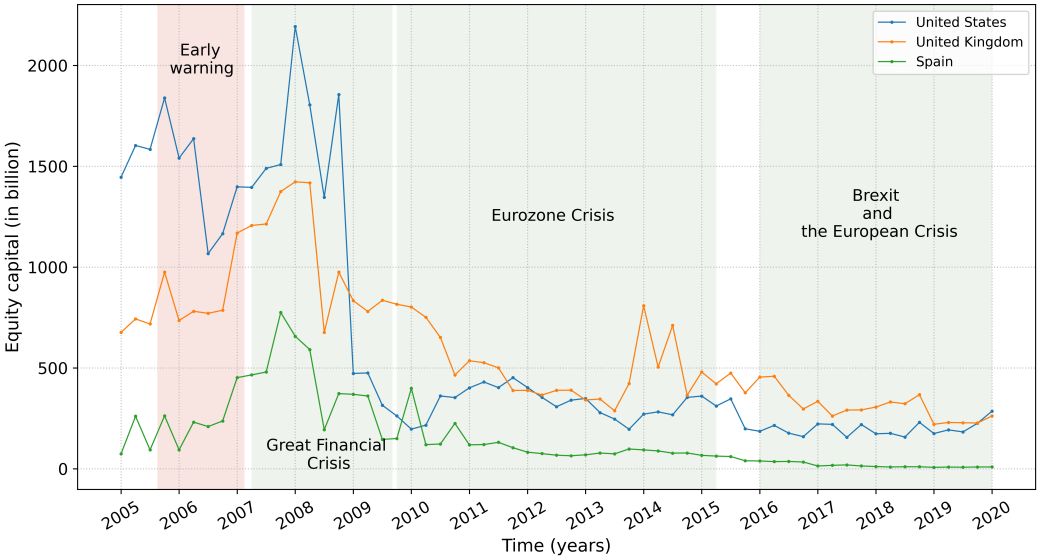
Note: The Figure exhibits the contagion process of the global banking system in response to the US banking system failure in 2005:Q4, 2008:Q1, 2011:Q2, and 2018:Q4. The black nodes indicate the defaulted banking systems with $\rho < 0.06$, the yellow nodes show banking systems with $0.06 < \rho < 0.09$, and the green nodes are banking systems with $\rho > 0.06$.

Source: Calculated by the author using BIS and IMF databases.[19]

[19]The Figure plotted using the network simulator developed by Dr. Simone Giansante.

Figure 2.11 is associated with Table A.2 in Appendix A.8 that reports the total domino losses of capital in the global banking system. Table A.2 reports that the US and the UK stand as the two most important countries and are followed generally by the Spanish banking system. Figure 2.12 plots the losses reported in Table A.2 to observe the dynamic of losses if any of the three top systemically important banking systems fail. By assessing the total global losses, Figure 2.12 shows a high percentage of losses by triggering mainly the US before the GFC in 2008. As it can be seen, regarding the US, global losses increased from $1,500 billion in 2005:Q1 and peaked at $2,301 billion in 2008:Q1. Since then the losses have dropped significantly and started decreasing to $500 billion in 2009:Q1. For the UK, global losses jump with a lag from $676 in 2005:Q1 to about $1,400 billion in 2008, and then it starts decreasing to the minimum at about $300 bn in 2020:Q1. Spanish banks also suffered $73 bn dollars in 2005:Q1 and then peaked at $774 bn in 2007:Q4. Since then, the losses declined to $193 in 2008:Q3. However, when the Eurozone crisis started in 2010, the losses jumped to $398 billion and kept decreasing to a minimum of around 9 billion dollars in 2020. Figure 2.12 is consistent with Figure 2.8 in the previous subsection and is aligned with the financial crisis within the sample period of 2005 and 2020.

FIGURE 2.12: Total loss of capital for the BIS cross-border banking systems



Note: Figure plots total loss of capital for the BIS cross-border banking system for the period between 2005:Q1 and 2020:Q1, when the 3 most systematically important national banking systems, i.e. the US, UK, and Spain, fail.

Source: Calculated and plotted by the author using BIS and IMF databases.

2.6 Conclusion

This study employs the eigen-pair network method to comprehensively analyze the properties and stability of the global banking system, focusing on 19 reporting BIS cross-border banking systems and utilizing sovereign-level balance sheet data spanning from 2005:Q1 to 2020:Q1. In contrast to the general market price-based systemic risk measure, which lacked early warning capabilities for financial crises, the spectral fixed-point eigen-pair approach proves more effective. This method offers a robust framework for investigating systemic risk and conducting macro-prudential analyses. It enables us to assess the overall behavior of the system, determine its stability, identify the most important and vulnerable institutions, and model the potential domino effects and negative externalities in case of a financial institution's failure.

Our investigation begins by examining the cross-border exposure of the banking system and visualizing the intricate interconnectedness within the cross-border financial landscape.

Furthermore, we delve into the moments of the degree distribution of the banking system network. This analysis reveals dynamic shifts in the network's topology, including in- and out-degrees, connectivity, and clustering coefficients. It becomes evident that the cross-border banking system tends to form clusters, contributing to an overall imbalance. Notably, a small number of national banking systems exhibit notably high degrees of connectivity, indicative of hub-like characteristics in the cross-border banking structure. This imbalance is further explored through the assessment of systemic importance and vulnerability using right and left eigenvector centralities. Our findings underscore the pivotal role of the United States and the United Kingdom, consistently emerging as key players within the global banking network. The top five countries contributing to financial system instability are identified as the US, UK, Spain, France, and Germany. Meanwhile, the top five systemically vulnerable countries encompass Japan, Spain, Switzerland, Germany, and France.

The examination of the proposed systemic risk index $\lambda_{max}(Q)$ provides profound insights into the cross-border banking network's instability and its connection to financial crises spanning 2005 to 2020. The sustained elevation of the maximum eigenvalue λ_{max} of the matrix Q beyond the stability threshold of 1 underscores significant systemic risk, highlighting the inherent instability of the global banking system throughout this period. Importantly, the patterns observed in $\lambda_{max}(Q)$ effectively anticipate impending crises, serving as an early warning signal. The analysis extends to the phenomenon of contagion within the cross-border banking system, vividly illustrating the dynamics of "too interconnected to fail" and "too big to fail". This visualization portrays how contagion propagates through the network, emphasizing the potential cascade effects stemming from the failure of systemically important banks.

In summary, the comprehensive evaluation of the instability systemic index, network connectivity, systemic importance, and contagion dynamics provides a holistic comprehension of the global banking system's stability and vulnerability. The observed patterns align with historical financial crises and underscore the urgency of addressing systemic risk and interconnectivity to safeguard the global financial landscape against future disruptions. Future research remains to broaden

this approach by incorporating the financial connections among sectors within individual countries and across sectors. This will require further modeling to understand how the repercussions of failure spread across Non-bank Financial Institutions (NBFIs) and non-banking sectors.

Chapter 3

Liquidity Contagion Analysis for Global Banking System Using Financial Network

Abstract. This chapter builds upon the analysis presented in Chapter 2, which utilizes quarterly balance sheet data from cross-border banking systems to examine the network of the Core Global Banking System (CGBS) across 19 reporting BIS countries from 2005 to 2020. This study focuses on assessing systemic risk related to liquidity in the core international banking system through the application of the network-based eigen-pair method. We use the liquid assets and short-term liabilities on the balance sheets to investigate liquidity issues within the global banking system. Our systemic risk index not only provided an early warning signal for the Global Financial Crisis (GFC) of 2007-2008 but also revealed the persistent instability of the system throughout the sample period, emphasizing the urgent need for measures to stabilize the system. Additionally, this chapter updates the ranking of systemically important and vulnerable banking systems using new variables. Our results continue to highlight the significant impact of the US and UK banking systems on systemic stability.

Keywords: Financial network, systemic risk, eigen-pair method, early warning signal, cross-border banking system, liquidity analysis.

3.1 Introduction

Global liquidity is a critical component of the international financial system and plays a significant role in shaping the dynamics of the global economy (Farmer, 2017; Aglietta, 2018). While global liquidity generally refers to the availability and ease of access to funds and credits in the international financial system, this chapter attempts to shed light on the nexus between the ability of market participants to operate cross-border flows and the overall stability of the cross-border banking system, especially in instances where the extensive exposure of the banking system can generate severe negative spillovers affecting the entire system (Domanski et al., 2011; Eickmeier et al., 2014). By extending upon the framework established by Markose et al. (2021) model and utilizing financial network analysis, this study leverages cross-border banking system data to investigate global liquidity and its systemic risk.

The 2008 financial crisis, characterized by a severe liquidity crunch, highlighted the importance of comprehending global liquidity and its implications. The 2008 financial crisis brought attention to the critical role of global liquidity as a transmission mechanism for financial shocks from a sector to the global financial market. Prior to the crisis, there was a period of abundant liquidity characterized by low interest rates and a search for yield environment. This phase led to a buildup of excessive leverage and risk-taking in the financial system, as investors and financial institutions sought higher returns by investing in complex and opaque financial products such as Collateralized Debt Obligations (CDOs), Mortgage-Backed Securities (MBSs), and various derivatives (Kamin and DeMarco, 2012). The interconnectedness of the global financial system allowed these toxic assets to be dispersed widely, creating a ripple effect throughout the system when the housing market bubble burst and subprime mortgage defaults surged. As losses mounted and uncertainty increased, global liquidity conditions quickly tightened, triggering a global financial panic, and financial institutions faced challenges in refinancing their short-term liabilities, resulting in a severe credit crunch that reverberated through the global economy. The crisis exposed vulnerabilities in the cross-border banking system, as international banks held

significant amounts of these toxic assets. When the value of these assets plummeted, it eroded the capital base of financial institutions, jeopardizing their solvency and eroding confidence in the banking system. The solvency and the interconnected nature of cross-border lending and financial derivatives amplified the contagion effects, rapidly spreading distress from one region to another. The need to model financial interconnectedness and the potential for systemic risk became evident, emphasizing the importance of analyzing global liquidity within the context of a financial network (Haldane, 2013).

In response to the crisis, central banks and governments implemented policies to restore global liquidity and stabilize financial markets. These actions included emergency liquidity facilities, interest rate reductions, capital injections into banks, and regulatory reforms to enhance financial stability. However, it is crucial to continuously assess the stability of the cross-border banking system and understand the countries or banking systems that contribute most to the instability of the global banking system. By systemic risk analysis in the cross-border banking system, policymakers and regulators can identify potential vulnerabilities and implement necessary safeguards to prevent future crises.

The contribution of this chapter is twofold; The first contribution lies within the realm of systemic risk analysis by extending the network-based eigen-pair method from Markose (2012) to investigate the systemic risk associated with liquidity issues across 19 core cross-border banking systems. This analysis draws from real-world balance sheet data obtained from the Bank for International Settlements (BIS) and the International Monetary Fund (IMF) from 2005 to 2020. Building upon the financial solvency exposure rate and the capital adequacy ratio utilized in the second chapter, this chapter also incorporates the liquidity ratio extracted from the balance sheets of the core cross-border banking systems to capture the financial institutions' exposure to liquidity risk. The second contribution to the existing literature is to establish the numerical rank order of the most systemically important and vulnerable banking systems within the cross-border framework. Our analysis demonstrates that adjusting the right and left eigenvector centralities of the generalized stability matrix by the total net liquid assets of

individual banking systems changes the identification of the most systemically important and vulnerable banking systems compared to the findings presented in the chapter 2.

In conclusion, this chapter seeks to enhance our understanding of global liquidity within the cross-border banking system. By examining the stability of this system, identifying countries that play significant roles, and exploring the vulnerabilities associated with it, this research contributes to the ongoing efforts to monitor and manage global liquidity risks. The structure of this chapter is as follows; In Section 3.2 we review the literature for the cross-border model and financial network. The methodology and the data are elaborated in Section 3.3. Section 3.4 illustrates the empirical results, and finally, Section 3.5 encompasses the achievement of the chapter.

3.2 Literature Review

Global Liquidity (GL) is an ambiguous term but generally can be defined as the "ease of financing from international sources". It can also reflect the ability of the global banking system and capital markets to fund financial assets (Caruana, 2014; Eickmeier et al., 2014). The concept of "ease of financing" is determined and characterized by market participants' attitudes and perceptions towards risk, valuations, and cash flows in the financial and money market that drive fund and credit extension and liquidity.[1] Thus, analyzing global liquidity dynamics is required to understand the participants and components of global liquidity (Bruno and Shin, 2015b; Cohen et al., 2017). While global liquidity is essential for economic growth,[2] it also poses several challenges. These challenges and issues can generate important externalities to the system and contribute to systemic risk. As GL is strictly linked to the International

[1]GL is then a general concept that captures a broad range of channels including the ability of corporations and FIs to fund investments, the capacity of firms in the process of securitization to access necessary financing to originate loans, to receive loans for packaging into securities, and finally to finance different kinds of guarantees (Cohen et al., 2017; Aglietta, 2018; Avdjiev et al., 2020).

[2]The important roles of global liquidity can be found here: (Farmer, 2017; Aglietta, 2018)

Monetary System (IMS) and seems as a critical factor for the stability of financial systems, analyzing its dynamic structure and its evolution clearly points out systemic flaws in the IMS.[3]

The Global Financial Crisis (GFC) stands as a notable instance of a global liquidity issue. In the 2008 financial crisis, as panic spread throughout the U.S. credit markets, frightened investors rushed to withdraw their money and deposits and sought refuge in safe assets. A shortage of "liquid" assets triggered a massive credit crunch that rendered the entire banking system susceptible to failure. The global financial meltdown of 2008 underscored the extent to which the banking system relied on short-term borrowing to finance its activities within the financial system. While using short-term debts to fund longer-term loans can be beneficial, it comes at the cost of banks facing default when short-term funding evaporates (Hartlage, 2012; Jobst, 2014; Roberts et al., 2018). Defaults in individual financial institutions can lead to cascading failures of others in an interconnected financial system (Glasserman and Young, 2016). Following the Global Financial Crisis (GFC), regulators aimed to reduce systemic risk in financial markets by enhancing macro-prudential policies and regulations. The Basel Committee for Banking Supervision initiated new financial requirements and global liquidity standards for the purpose of creating a more resilient global banking system, particularly when addressing issues of liquidity.[4]

The Basel Committee has mainly developed two liquidity ratios to promote the system's stability (see BCBS (2010)). The Liquidity Coverage Ratio (LCR)[5] is designed to guarantee

[3]There is one strand of literature covers the development of global liquidity in post-GFC crisis and reveals the upcoming risk of new episodes of liquidity crunch, warns of the negative spillovers for economies and difficulties for managing GL, which undoubtedly would impose very high costs in the global economy. Several of these challenges to global liquidity are explained in Appendix A.9.2. These include (1) liberalisation and global imbalances; (2) chasing yields and carry trade; (3) Monetary market spillovers (e.g. unconventional monetary policies and quantitative easing (QE)). For more details of the literature, see Kindleberger and Kindleberger (1978); Kindleberger (1991); Acharya et al. (2013, 2014); Shin (2014); Boyson et al. (2014); Turner (2014); Micossi (2015); Acharya and Steffen (2015); Boyson et al. (2016); Evans-Pritchard (2016); Hannoun and Dittus (2017); Icard and Turner (2019); Kashyap and Stein (2023)

[4]Basel III post-crisis reforms, which was an internationally agreed set of measures, is the last regulation that was introduced to increase the overall (resilience of) financial system stability in response to the crisis.

[5]The LCR is the ratio of the bank's stock of unencumbered HQLA to its projected net cash outflows during 30 days. LCR is generally designed to measure the ability of an institution to withstand a stressed funding scenario (a severe liquidity freeze) (Roberts et al., 2018).

that banks hold sufficient stock of high-quality liquid assets (HQLA)[6]. Likewise, the Basel III accord addressed structural resilience through another liquidity ratio, the Net Stable Funding Ratio (NSFR). The implementation of these liquidity ratios is expected to address maturity mismatch issues, subsequently reducing systemic risk (Allen et al., 2017; Brunnermeier and Krishnamurthy, 2014; Adrian and Boyarchenko, 2018; Cecchetti and Kashyap, 2018).[7]

A growing literature study the problem of maturity mismatch in destabilizing the financial market begins with early works of Leland and Pyle (1977) and Townsend (1979), which focused on financing and contracting problems in bank lending. Subsequent studies, such as Goodhart et al. (2008), Strahan (2008), Hartlage (2012), Jobst (2014), Gale and Gottardi (2015), and Roberts et al. (2018), continued to explore iquidity issue. Following the Basel Accords in post-GFC, some studies like Jobst (2014) and Roberts et al. (2018) underscore the necessity of incorporating liquidity ratios into the systemic risk indices. This chapter expands the network-based eigen-pair Systemic Risk Index (SRI) using the concept of liquidity ratios to capture the effect of maturity mismatches and liquidity risk.

Additionally, it is essential to specify the particular component of global liquidity under discussion when investigating the broad concept of global liquidity. GL is typically formed by the interaction between the three different components; the asset-liability point of view, the private-official interactions, and the national-international components (Icard and Turner, 2019). The asset-liability point of view is very useful for measuring the degree of global liquidity. The total amount of credits and the extension of credit can be determined by the asset side or the liability side of the balance sheet of financial institutions. Secondly, the level of liquidity also depends on the interaction of the public sector and private investors, where the key difference is mainly characterized by the source and dynamic of liquidity. Private liquidity is a key factor in

[6]HQLA is defined as assets or cash that can be quickly altered into cash without loss of value through sales or being pledged as collateral. This allows FIs to survive a significant liquidity issue over a 30-day stress period.

[7]NSFR is calculated by dividing the available amount of stable funding by the required amount of stable funding at least for a one-year period; deposits, long-term wholesale funding, and equity are considered as stable funding. The NSFR aims to show risks that can happen from significant maturity mismatches between liabilities and assets.

risk exposures in the global financial market as it quantitatively dominates the public sources of liquidity and it is actually the main component that tends to evaporate during financial crises and then liquidity collapses into the official part (Domanski et al., 2011; Landau, 2018; Ghymers, 2019; Icard and Turner, 2019). Finally, our focus is on addressing the international dimension of liquidity, rather than the national aspect. The BIS consolidated balance sheet data that is applied in this study is helpful in highlighting all three components of liquidity.

One strand of the literature covers cross-border exposure of banks which is a component of the private liquidity that is intimately linked to global liquidity dynamics. The cross-border banking system is playing a key role in financial intermediation and facilitating cross-border transactions, acting as a conduit for liquidity transmission across borders. The high exposure of European banks to the US securitized assets led to a 50% equity capital loss (around $1.6 trillion) underscoring the role of cross-border exposures in the dynamic of the 2007 crisis (Allen, 2011). Other studies on the drivers of cross-border capital flows can be found in Milesi-Ferretti and Tille (2011), Powell et al. (2013), and (Shin, 2014), where the literature explores intricacies of capital flows, considering factors beyond interest rate differentials, such as expected investment returns, economic growth, and institutional frameworks. Additionally, the procyclical nature of capital flows and the risks they pose, along with cross-border contagion and spillovers, are examined extensively (see Claessens and Forbes (2001); Haldane (2009); Allen (2011); Minoiu and Reyes (2013); Castrén and Rancan (2014); Ghymers (2017)).[8]

Another aspect of the literature focuses on Systemic Risk Indices (SRIs) used in evaluating financial system exposure risks. Section 2.2 elaborates on two main categories of SRIs, balance sheet network-based SRIs and market price-based SRIs, with a preference shown towards balance sheet network-based spectral SRI rather than popular market price-based SRIs such as Marginal Expected Shortfall (MES), Delta Conditional Value-at-Risk (ΔCoVaR), and Conditional

[8]The extensive literature on cross-border exposures explained in Section 2.2, Chapter 2.

Capital Shortfall Measure of Systemic Risk (SRISK).[9] This choice can also be attributed to the holistic reflection of financial institutions' conditions in the market, particularly concerning the asset-liability components of global liquidity. The balance sheet serves as a direct window into the institutions' positions. Moreover, this aligns with the nature of liquidity ratios in the context of the Basel III accord, which predominantly rely on balance sheet indicators (Jobst, 2014; Roberts et al., 2018).

In conclusion, global liquidity, shaped by financial flows and the cross-border banking system, is crucial for the functioning of the global economy. However, managing global liquidity poses challenges that can be seen in the global financial market and ongoing discourse calls for comprehensive policy responses to address the challenges posed by global liquidity spillovers. The Working Party and Policymakers call for a sufficient framework to monitor and regulate systemic risk carefully to maintain stable and sustainable global liquidity (see Domanski et al. (2011), (Castrén and Rancan, 2014), and Icard and Turner (2019) for the extensive discussion). This study seeks to contribute by modeling global liquidity within a cross-border banking system, analyzing the systemic risk, and assessing important and vulnerable components of the system.[10]

3.3 Methodology and Data

This section highlights two theoretical parts of studying the financial network of cross-border banking systems. The first part elaborates on constructing the financial network for the banking system, and the second part explains the framework for the contagion and stability analysis of the system.

[9] Delta Conditional Value-at-Risk (ΔCoVaR), and Conditional Capital Shortfall Measure of Systemic Risk (SRISK) that are mainly introduced by Adrian and Brunnermeier (2011) and Acharya et al. (2012, 2017). See Section 2.2 in Chapter 2 for more details on balance sheet network-based SRIs and market price-based SRIs.

[10] This section provides a brief review of the extended literature on global liquidity, presented in Appendix A.9.2. For further details and insights into the related literature, see A.9.2.

3.3.1 Financial Network Analysis for Cross Border Model

To analyse the banking systems and liquidity circulation using network science, we first build a directed weighted network with N number of nodes (vertices) which are connected by E set of linkages (pair of finite sets (N,E)). In this context, every national banking system from BIS reporting countries is represented as one node and their corresponding links are determined by directional bilateral debt relationships (borrowing/lending) between each banking system. In this regard, gross flows in $N \times N$ matrix are built, where each element x_{ij} denotes the direct link that shows the flows of claims (or, liabilities) from FI i to counterparty j. These links or edges are also known as out-degree and in-degree linkages which indicate respectively the flow of claims (payments or financial obligations) to and from each FI (Markose, 2012; Degryse et al., 2010).

$$X = \begin{pmatrix} 0 & x_{12} & ... & ... & ... & x_{1N} \\ x_{21} & 0 & ... & ... & ... & : \\ : & : & 0 & ... & ... & : \\ : & : & : & 0 & ... & : \\ : & : & : & : & 0 & x_{iN} \\ x_{N1} & : & : & : & x_{Nj} & 0 \end{pmatrix} \tag{3.1}$$

The netted *skew symmetric matrix* of M is constructed with entries $N_{ij}^{+} = N_{ij}^{-}$, where $N_{ij} = (x_{ij} - x_{ji})$ indicates the netted liabilities' position between counterparties i and j. If N_{ij} is positive, net financial claims are from banking system i to counterparty j is x_{ij}. Otherwise, the net negative liabilities are zeros. For the network analysis of the systemic risk and contagion process, the entries only with positive netted positions (N_{ij}^{+}) and zero are used in the network of counterparties i to j to evaluate the system's instability by defaulting one banking system in meeting its obligations from banking system i to banking system j.

For analysing the systemic risk of liquidity using the financial network, we extend the model described in Chapter 2 by introducing the short-term components of banking systems' balance sheets; current liabilities and high-quality liquid assets. The balance sheet of the banking system contains short-term obligations that can contribute to the system's instability, however, this can be mitigated by liquid assets. The positive netted position N_{ij}^{+} then is adjusted by the netted high-quality liquid assets H_i and can be defined by $H_i^N = H_i - L_i$. This term captures the role of liquid assets in the banking system and forms the financial network corresponding to global liquidity. The positive netted position of matrix N_{ij}^{+} then is adjusted by the netted liquid assets as follows,

$$M_{ij}^{+} = max([N_{ij}^{+} - H_i^N], 0) \tag{3.2}$$

where the elements of M_{ij}^{+} are the direct links that show the positive flows of liabilities from banking system i to counterparty j easing by the liquid assets. N_{ij}^{+} denotes the positive net liabilities of banking system i to participant j, and H_i^N is the netted liquid assets position for country i. In this context, the so-called stability matrix Θ represents the positive entries for net liquidity from FI i to counterparty j relative to denominator C_j, where C_j is the Tier 1 capital for banking system j that is adjusted proportionately for foreign exposure.

$$\Theta = \begin{pmatrix} 0 & \frac{M_{ij}^{+}}{C_{20}} & ... & ... & ... & \frac{M_{ij}^{+}}{C_{N0}} \\ \frac{M_{ij}^{+}}{C_{10}} & 0 & ... & ... & ... & : \\ : & : & 0 & ... & ... & : \\ : & : & : & 0 & ... & : \\ : & : & : & : & 0 & \frac{M_{ij}^{+}}{C_{N0}} \\ \frac{M_{ij}^{+}}{C_{10}} & : & : & : & \frac{M_{ij}^{+}}{C_{j0}} & 0 \end{pmatrix} \tag{3.3}$$

3.3.2 Network Stability Analysis

Once the stability matrix has been constructed, the transmission of contagion through the financial system is characterized in the mathematical form:

$$\begin{aligned} u_{it+1} &= [\frac{L_i}{H_i} - \rho]u_{it} + \sum_j \frac{M_{ji}^+}{C_{i0}} u_{jt} \\ u_{it+1} &= [\frac{L_i}{H_i} - \rho](1 - \frac{C_{it}}{C_{i0}}) + \sum_j \frac{M_{ji}^+}{C_{i0}} u_{jt} \end{aligned} \tag{3.4}$$

where u_{it+1} represents the dynamics for the possible default rate of banking system i at time $t+1$ which can mainly arise from two sources; the first term captures the rate at which a banking system does not survive due to the liquidity and capital insufficiency of a bank (node) i in the network. $\frac{L_i}{H_i}$ is the encumbered liquidity ratio, which captures the liquidity risk, the variable L_i is the current liabilities (short-term liabilities) and H_i is the high-quality liquid assets.[11] ρ is the cure rate of capital, and thus $(\frac{L_i}{H_i} - \rho)$ is the rate of instability due to the insufficient liquid assets and cure rate (Gallagher and Andrew, 2003; Chakrabarti et al., 2008; Tracy and Tracy, 2014).[12] Further, u_{it} is the cumulative loss of capital for banking system i at time t. Thus, it can be defined as $(1 - \frac{C_{it}}{C_{i0}})$ $\forall t > 0$. Here, C_{it} shows remaining resources (Tier 1 capital) for banking system i at time t, and C_{i0} is also the initial resource. Hence, the component $(1 - \frac{C_{it}}{C_{i0}})u_{it}$ represents the degree to which the counterparty i is not able to mitigate its default using the cure rate, ρ.

The second factor of instability that can affect the default rate of banking system i arises from the interconnections between banking systems in the network and is defined by $\sum_j \frac{M_{ji}^+}{C_{i0}} u_{jt}$, where this term captures the weighted sum of the heterogeneous ratio of being suffered at time t arising from the bilateral net of exposures of FI i to those of counterparties j and adjusted by the capital and liquid asset of FI i. u_{jt} is the representative of weights for the individual rates

[11] The ratio $\frac{L_i}{H_i}$ captures the liquidity shock and is similar to the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) introduced by Basel III and explained in the Section 3.2.

[12] Similar concept used in Heath et al. (2016) that study the role of CCP in the market.

of default for counterparty j. The contagion dynamics in Equation 3.4 also can be written in matrix notation as follows:

$$U_{t+1} = \underbrace{[D^{Liq} - D^{Sol} + \Theta^{'}]}_{\mathrm{Q}} \; U_t \tag{3.5}$$

where U_t denotes a vector of u_{it} for $i = 1, ..., N$ and shows the potential default rate in the interbank network. the matrix $\Theta^{'}$ denotes the transpose of stability matrix Θ with elements $\theta^{'}_{ij} = \theta_{ij}$, The matrices D^{Liq} and D^{Sol} are the diagonal matrices with the encumbered liquidity ratios and the capital loss thresholds for each banking system, respectively. The system stability of equation 3.5 then can be analyzed on the basis of power iteration of matrix Q. Therefore, Equation 3.5 can yield the following form:

$$\begin{aligned} U_t &= [D^{Liq} - D^{Sol} + \Theta^{'}]^t \; U_0 \\ U_t &= Q^t \; U_0 \end{aligned} \tag{3.6}$$

Once the channels of risk are identified in the eigen-pair model, the system stability can be analysed based on the tipping point 1 if $t \to \infty$. Thus, the stability condition is satisfied if,

$$\lambda_{max}(Q) = \lambda_{max}(D^{Liq}) - \lambda_{max}(D^{Sol}) + \lambda_{max}(\Theta^{'}) < 1 \tag{3.7}$$

where $\lambda_{max}(Q)$ not only capture the systemic risk of the system. According to the stability condition 3.7, the banking system with a high encumbered liquidity ratio and low capital loss can contribute more to the instability of the system. This condition is the extended stability condition of Equation 3.7 in Chapter 2, Section 2.3. The concept of $\lambda_{max}(\Theta^{'})$ and its associated right and left eigenvector that we explained in Section 2.3 is still held. We will report the liquidity results relating to right and left eigenvector in Section 3.4.

3.3.3 Data

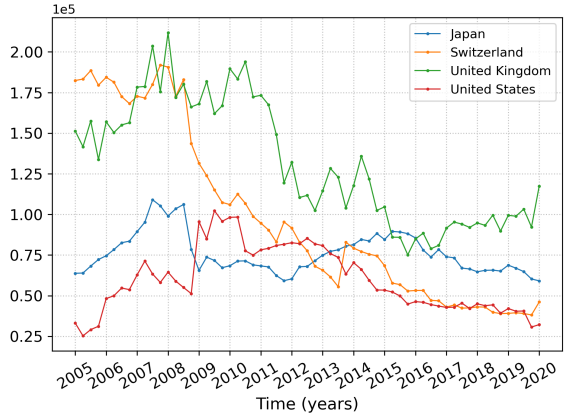
The data description of solvency variables including receivables, payables, and Tier 1 capital is already explained in Chapter 2, Section 2.4. In this section, we describe the two variables liquid assets and short-term liabilities that are required for the examination of liquidity in a cross-border banking system. The liquid assets and short-term liabilities are taken from the IMF database.[13] Liquid assets here are considered assets, which are readily available to a FI to meet a demand such as paying off short-term obligations. In order to classify a financial asset as liquid, the FI must make sure that the asset can be converted immediately into cash without significant loss with reasonable certainty. Liquid assets taken from the IMF dataset comprise three classes: (i) currency; (ii) deposits and financial assets that are available either on demand or within three months; and (iii) securities that are traded in liquid markets (including repurchase agreement markets).

High-quality liquid assets for 19 BIS reporting countries are shown in Figure 3.1. The figure shows that France, the UK, Swiss, Japan, and the Netherlands with an average of 200, 131, 98, 75, and 62 billion dollars are the top 5 banking systems with the highest liquid assets, respectively. The US stands on rank 6 with an average of 59 billion dollars. The lowest high-quality liquid assets on average are concerned with Portugal ($1.5 bn), Finland ($2 bn), Turkey ($2.6 bn), Greece ($5 bn), and Australia ($10 bn).

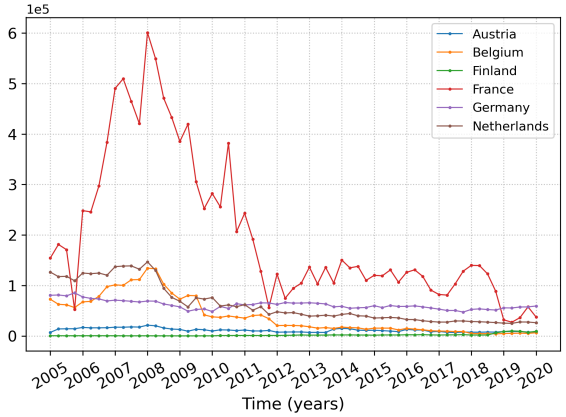
[13]The IMF data can be found in https://data.imf.org.

FIGURE 3.1: High-quality liquid assets time series

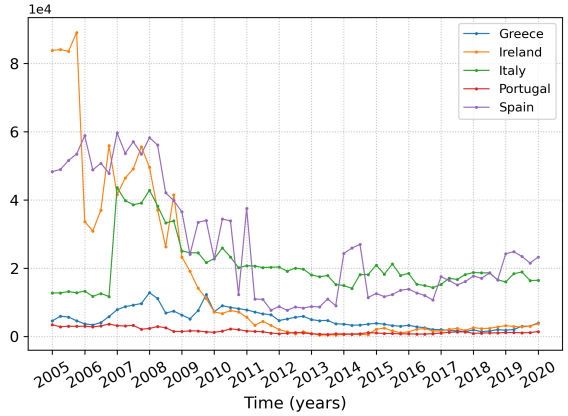
(A) Core economies



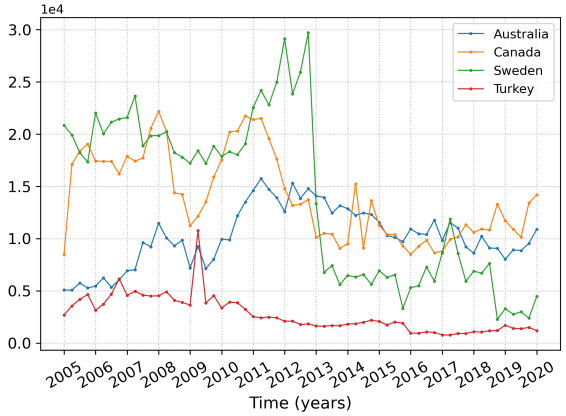
(B) EU non-GIIPS economies



(C) GIIPS economies



(D) Other economies



Note: Figure exhibits quarterly high-quality liquid assets in million US dollars for BIS reporting Banking systems between 2005:Q1 and 2020:Q1. France, the UK, Swiss, Japan, and the Netherlands are the countries with the highest high-quality liquid assets with an average of 200, 131, 98, 75, and 62 billion dollars. "e" means exponent and 1e4 and 1e5 are the scientific notation which means 10 to the power of 4 and 5, respectively.

Data source: Plotted by the author using IMF database.

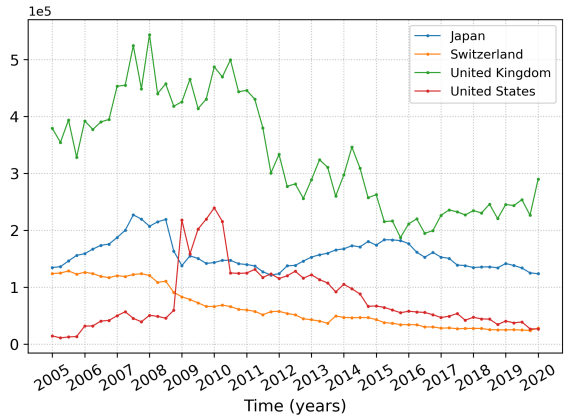
Current liabilities of cross-border banking systems are also considered the short-term element of deposit takers' debt liabilities and the net (short-term) market value financial derivatives position (liabilities fewer assets).[14] As it can be seen in Figure 3.2, the United Kingdom, France, Japan, Spain, and the United States are the top 5 countries with short-term debt with 332, 312, 157, 118, and 79 billion dollars on average. The countries with the least short-term

[14]Here "short-term" can be defined as one year or less, so short-term liabilities are the liabilities that are calculated for three months or less.

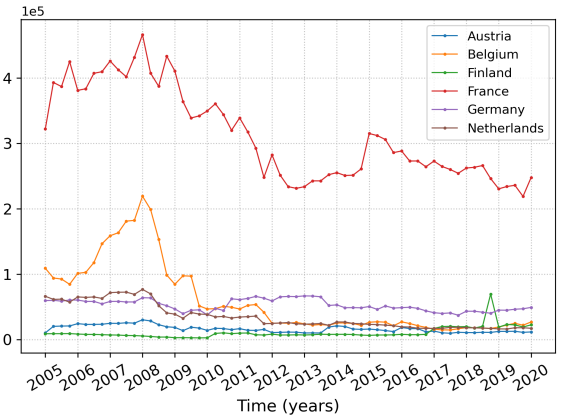
liabilities are respectively Turkey, Finland, Greece, Portugal, and Austria with 3, 10, 11, 14, and 16 bn dollar liabilities.

FIGURE 3.2: Short-term liabilities time series

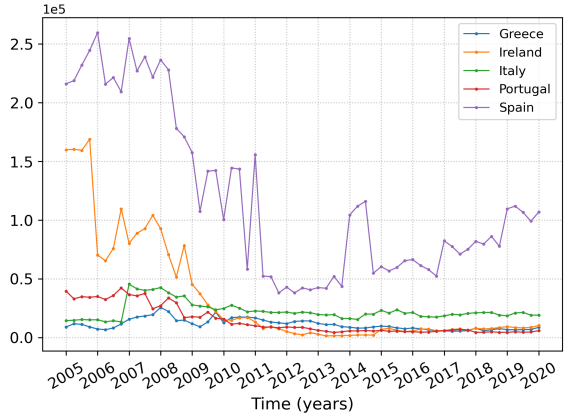
(A) Core economies



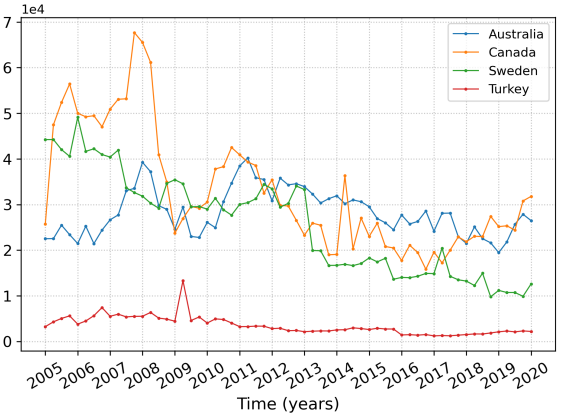
(B) EU non-GIIPS economies



(C) GIIPS economies



(D) Other economies



Note: Figure exhibits quarterly short-term liabilities in million US dollars for BIS reporting Banking systems between 2005:Q1 and 2020:Q1. The United Kingdom, France, Japan, Spain, and the United States are the top five countries with the highest high-quality liquid assets with an average of 332, 312, 157, 118, and 79 billion dollars. "e" means exponent and 1e4 and 1e5 are the scientific notation which means 10 to the power of 4 and 5, respectively.

Data source: Plotted by the author using IMF database.

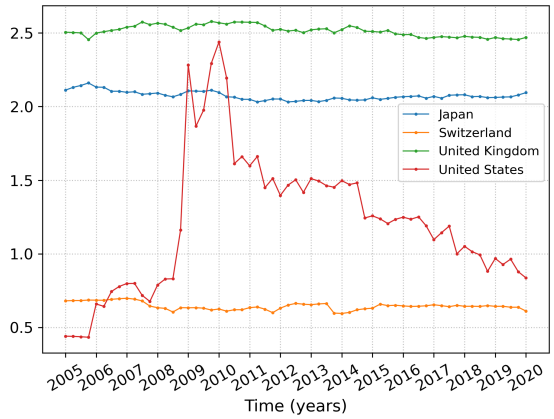
Nevertheless, the focus of the analysis lies not on individual analysis of liquid assets or short-term liabilities in isolation, but rather on examining the extent to which high-quality liquid assets align with current liabilities. We thus evaluate the proportion of current liabilities in relation to high-quality liquid assets and report the encumbered liquidity ratio of each banking system in Figure 3.3. The ratio of short-term liabilities to liquid assets in Figure 3.3 captures the liquidity mismatch of liabilities and assets and shows an indication of the

extent to which each country is able to meet its short-term obligation without facing liquidity issues. According to the sample data, among all the banking systems, Finland, Portugal, Spain, Australia, Ireland, and the United Kingdom have the highest encumbered ratios, with their short-term debt exceeding their liquid assets by more than 9.5, 8, 4.5, 3, and 2.7 times, respectively. However, the Netherlands, Switzerland, and Germany have the lowest encumbered ratios among all the countries, with ratios of 0.58, 0.64, and 0.85, respectively, indicating that their debt is relatively lower compared to their liquid assets. Italy and the United States rank 4th and 5th, respectively, with encumbered ratios of 1.1 and 1.2. Despite having relatively lower liquid assets compared to their debt, they are still among the top 5 lower encumbered ratios.[15]

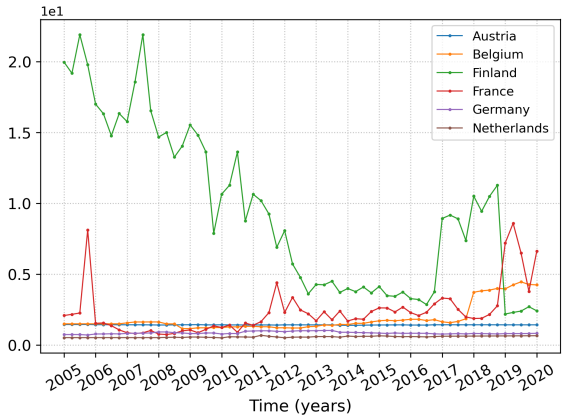
[15]Note that this study ranks the banking system without controlling by the credit rating since it is mainly an ex-post analysis, focusing on deriving data and information from historical data. The data utilized in this analysis directly extracted from the balance sheets of various banking systems, inherently capturing the credit rating associated with each respective system.

FIGURE 3.3: Encumbered Liquidity ratio time series

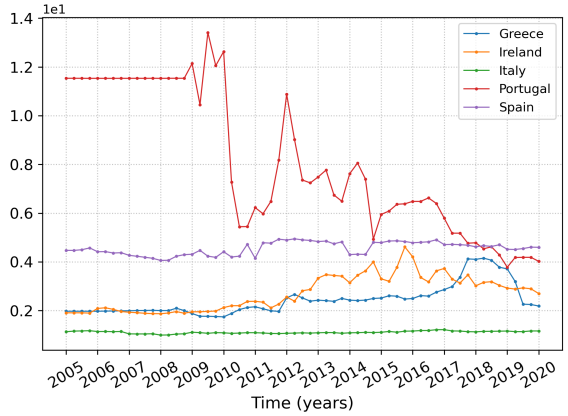
(A) Core economies



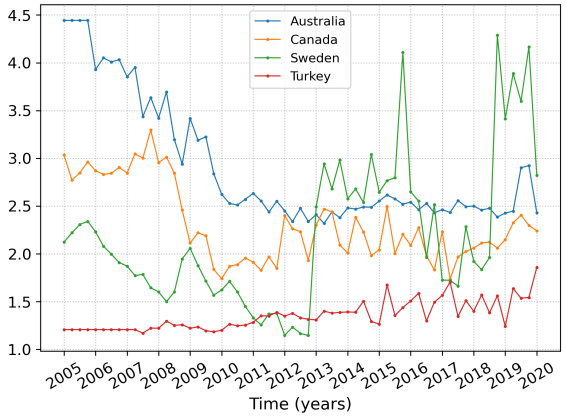
(B) EU non-GIIPS economies



(C) GIIPS economies



(D) Other economies



Note: Figure exhibits quarterly encumbered liquidity ratio for BIS reporting Banking systems between 2005:Q1 and 2020:Q1. Finland, Portugal, Spain, Australia, and Ireland are the top five countries with the highest encumbered liquidity ratio with the average of 9.5, 8, 4.5, 3, and 2.7, respectively.

Data source: Calculated and plotted by the author using IMF database.

3.4 Empirical Results: Cross-border Network Analysis

We analyze the system stability in the cross-border banking system network by applying the data explained in Section 2.4 and 3.3 in the framework 3.3. We introduce the systemic risk index and then identify the systemically important and the systemically vulnerable countries by decomposing the eigenvalue of the network. The systemic risk index and connectivity plot in Figure 3.4 during 2005:Q1 and 2020:Q1.

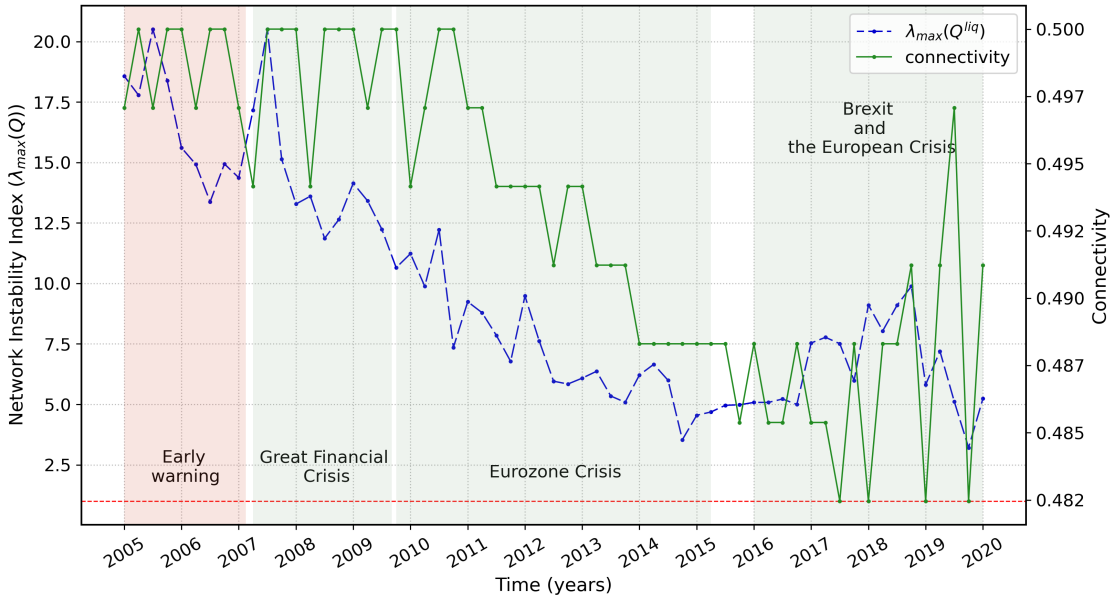
The systemic risk index depicted in Figure 3.4 provides insights into the instability of the financial system during the sample period. The maximum eigenvalue ($\lambda_{max}(Q)$) indicates the overall system instability both in the pre-crisis and post-crisis 2008 periods, aligning with the incidents and conditions observed in the financial market from 2005 to 2020. The instability index implies the degree of instability of the net liabilities mitigated by the remained liquid asset which is adjusted by the Tier 1 capital of the exposed national banking system. The figure shows that the index is at its highest at about 20 in late 2006 in the pre-crisis period which can be interpreted as an early warning signal in the banking system stability. At the beginning of the crisis in early 2007 before the crisis deepened, the signal once again peaked at 20. Since then, the index started decreasing continuously to its lowest at about 3.5 in late 2015, and then the index again amplified with Brexit and the European crisis. In early 2016, the United Kingdom voted to leave the European Union and fueled concerns across the market. Thus, investors fled to safety assets and pushed yields to negative values. In mid-2016, 17% of loans ($400 billion) in Italian banks staggered, and banks required a bailout. This crisis is along with the increase of eigenvalue in post-2016. The index shows that even though the index decreases during the sample period and the banking system becomes more stable, the system as a whole is very unstable from 2005 to 2020. In the early stage of GFC, the index is about 20 times more unstable than the threshold, but after the reduction in the systemic risk, the system is still 3.5 times more unstable than the stability condition 1.

The connectivity metric also implies the likelihood of a connection between two banking systems by cross-border flows, reflecting how dense the system is connected. Figure 3.4 illustrates that the ranges of connectivity during the whole period are (0.48,0.50) which are moderate connections.[16] It also shows that there is a moderate positive correlation between connectivity and stability of the network within the sample period, which implies that as the connectivity decreases over the sample from 2005 to 2020, the instability of the system reduces. The main

[16]The definition and formula of the connectivity can be found in Appendix A in Annex A.5

reduction in systemic risk can be due to a positive correlation with the connectivity for the period 2010 to 2015.

FIGURE 3.4: Connectivity and network instability indices



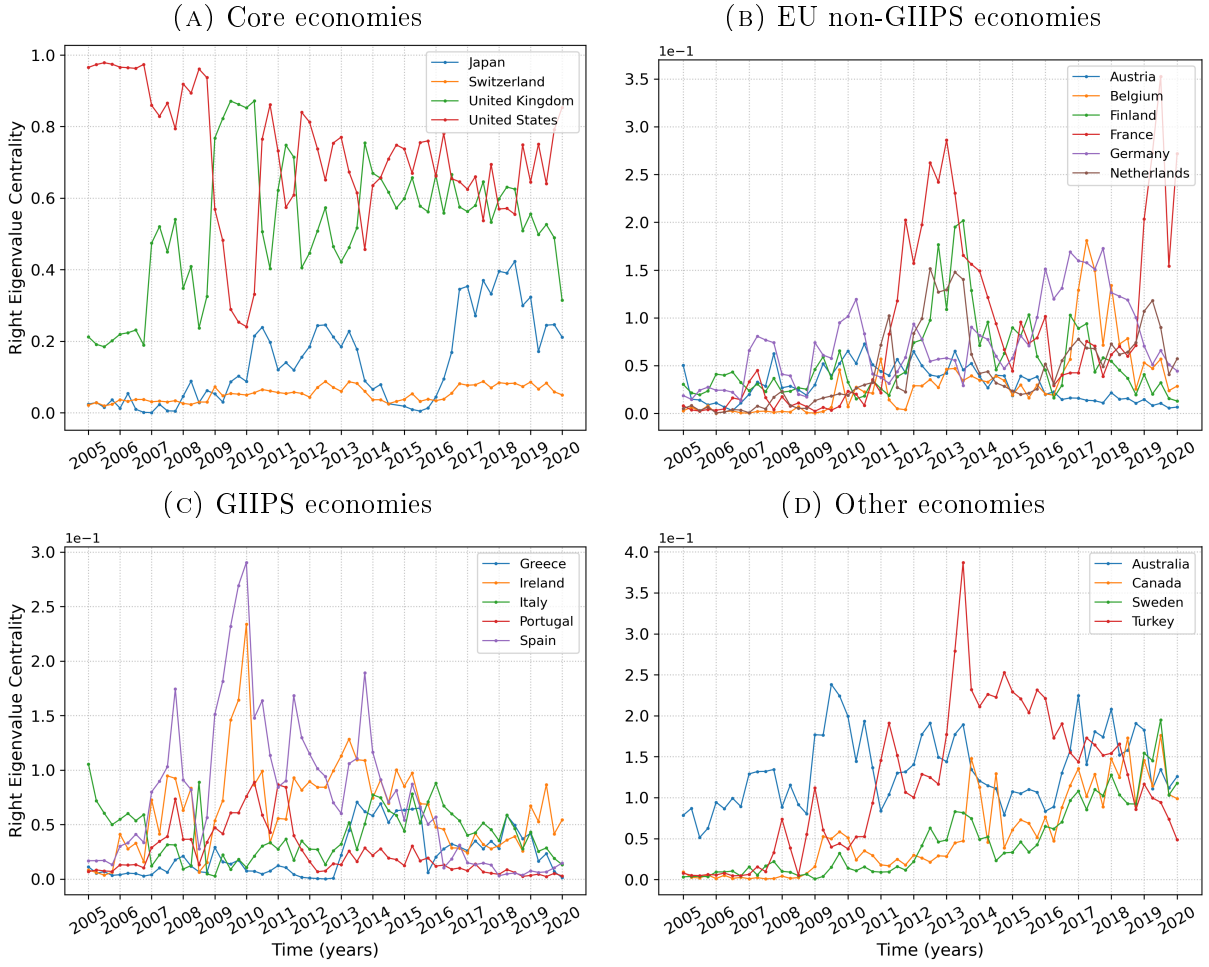
Note: The Figure plots the connectivity and network instability index from 2005:Q1 to 2020:Q1 for the BIS reporting countries. The left axis represents the network instability index, and the right axis shows the connectivity. The red dashed line represents the threshold of system stability.

Data source: BIS consolidated banking system statistics.

Once we examine the stability of the system, we attempt to discuss the contribution of each banking system to the instability of the network. Figure 3.5 reports the dynamics of right eigenvectors of the matrix Θ corresponding to $\lambda_{max}(\Theta)$ and ranks the importance of banking system within the system (Markose, 2012). Figure 3.5 shows that the US, UK, Japan, Australia, and Turkey are the top systemically important banking system with the right eigenvector centrality 0.71, 0.52, 0.13, 0.13, 0.11. The figure explains the role of the US in imposing the systemic threat in the GFC. Following the 2008 crisis, the growing patterns observed in the right eigenvectors associated with the UK, EU, and GIIPS economies can also potentially reflect the Eurozone crisis between mid-2009 and 2015. Additionally, the least systemically important banking systems based on their respective right eigenvector centralities include Greece, Portugal, Austria, Belgium, and Italy, with centralities of 0.02, 0.025, 0.030,

0.032, and 0.04, respectively. Our findings are still consistent with the previous findings about the threatening role of the US and UK and studies such as Furfine (2003) and Degryse et al. (2010). The high systemic threat posed by Turkey is also evident in Figure 3.5(D), indicated by the significant volume of liabilities it holds with its counterparties. Regarding the claims on Turkey, Figure A.6 reports that the leading countries holding claims are the US, Greece, Germany, and France with 22.7, 18.4, 15.2, and 11.9 percent, respectively.

FIGURE 3.5: Dynamic of systemic importance (right eigenvector centrality)



Note: The Figure shows the systemically important banking systems based on right eigenvector centrality from 2005:Q1 to 2020:Q1. The top 5 systemic important countries are the US, UK, Japan, Australia, and Turkey, respectively.

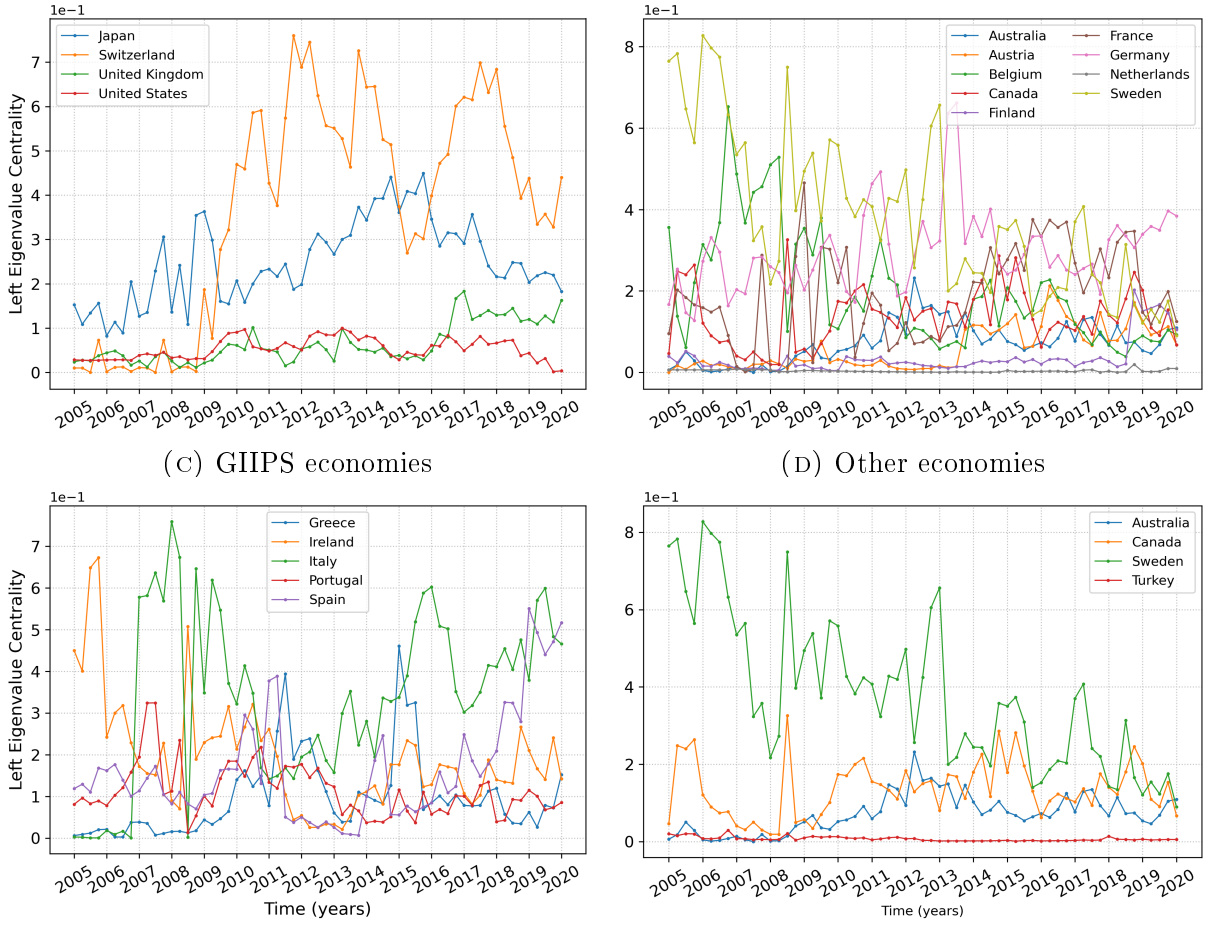
Source: Calculated and plotted by the author using BIS consolidated banking system data.

Figure 3.6 also reports the vulnerability of global banking systems by evaluating the evolution of left eigenvector centrality during the sample period. This indicator represents the effect of

the exposures of each bank to other banks as Markose (2012) mentioned. Based on the average left eigenvector centralities calculated for the period of 2005 to 2020, the top vulnerable banking systems are Sweden, Switzerland, Italy, Germany, and Japan, with centralities of 0.38, 0.36, 0.33, 0.29, and 0.25, respectively. The left eigenvector centrality also echoes the vulnerability of Eurozone banking systems throughout the sample period. Notably, Figure 3.6(B) and (C) indicate that the recapitalization of core Eurozone banks has contributed to reducing their vulnerability indexes. However, a notable divergence arises with Italy, marked by a significant 17% reduction in loans (equivalent to $400 billion) within Italian banks around mid-2016, distinguishing it from other European countries. The figure also shows the increasing trend in exposure for the Swiss banks, notably holding the liabilities from the US, UK, Germany, and France at rates of 45.4%, 26.5%, 11%, and 6.3%, respectively (see Figure 2.5(B)). This pattern should serve as a warning signal for Switzerland, indicating a significant level of exposure to these economies. Besides, at the lower end of the spectrum in terms of systemic vulnerable baking systems, we have the Netherlands, Turkey, Finland, the United States, and Austria, each with average left eigenvector centralities of 0.003, 0.007, 0.03, 0.05, 0.06.

FIGURE 3.6: Dynamic of vulnerability index (left eigenvector centrality)

(A) Core economies (B) EU non-GIIPS economies



(C) GIIPS economies (D) Other economies

Note: The Figure plots systemically vulnerable banking systems based on left eigenvector centrality from 2005:Q1 to 2020:Q1. The top 5 systemic vulnerable countries are Sweden, Switzerland, Italy, Germany, and Japan, respectively.

Source: Calculated and plotted by the author using BIS consolidated banking system data.

3.5 Concluding Remarks

This study analyzes the properties and stability of the global liquidity between 19 reporting BIS banking systems using their balance sheet data for the period 2005:Q1 and 2020:Q1 based on the eigen-pair method. The spectral eigen-pair approach is used over the general market price-based systemic risk measure since the latter failed to provide early warning signals of the financial system crises. This method provides a powerful framework to investigate systemic

risk and macro-prudential analyses that can give information on identifying the most systemic important and the most vulnerable institutions, as well as specifying the behavior of the system as a whole and identifying if the system is growing stable or unstable. The approach also explains the domino effects and the negative externalities of the system if an institution fails.

This chapter uses the liquid assets and short-term liabilities to study the stability of liquidity in the core global banking systems reported by BIS organization. Using the systemic risk index $\lambda_{max}(Q)$, this chapter has shown that this method still provides an early warning of systemic risk. Our result also shows that while the eigen-pair SRI reflects that the global banking system has become more resilient, the index represents the instability of the system throughout the sample period and calls for immediate action to make the system stable. The systemically important banking systems as well as systemically vulnerable countries have been identified during the sample period. While our results for solvency indicate that the top 5 systemic important countries are the US, UK, Spain, France, and Germany, respectively, the liquidity shows that the US, UK, Japan, Australia, and Turkey are the top systemically important banking systems. Furthermore, considering only the solvency, the top 5 systemic vulnerable countries are also Japan, Spain, Switzerland, Germany, and France, respectively. However, based on the average left eigenvector centralities calculated for the period of 2005 to 2020, the top vulnerable banking systems are Sweden, Switzerland, Italy, Germany, and Japan. Our results also declare that once the interconnectedness between banking systems decreased, the system became more stable over the period 2005:Q1 and 2020:Q1. Future research should initially focus on analyzing the contagion within the current extended model. Subsequently, it should aim to enrich this approach by integrating financial connections among sectors within individual countries and across diverse sectors. This necessitates further modeling of Non-bank Financial Institutions (NBFIs) and non-banking sectors.

Chapter 4

The Origin of Aggregate Fluctuation in a Network Economy: Liquidity Issue

Abstract. This chapter investigates liquidity dynamics in financial and monetary markets, particularly within a network economy, emphasizing the importance of understanding liquidity for financial stability and economic health. The research utilizes the Structural Vector Autoregression (SVAR) model and employs both Cholesky decomposition and B-model identification to analyze causal relationships and capture complex dynamics in the US economy. The study highlights the significance of disruptions in debt payments by firms and the role of the money market in financing current liabilities. The findings also reveal the crucial role of the quick ratio and network effect in the economy's business cycle, compared to other variables. Robustness checks using different identification methods and network measures validate the reliability of findings. Policymakers, regulators, and market participants can utilize these insights to manage liquidity risks effectively and establish resilient frameworks, promoting market stability and overall economic well-being.

Keywords: Liquidity, Business cycle, aggregate volatility, SVAR, input-output linkages, intersectoral network.

4.1 Introduction

Financial and monetary markets are typically characterized by the level of liquidity that firms need to meet their obligations, which generally involve assets and liabilities with relatively short maturities or durations. In an economy where firms engage in frequent trading and possess short-term assets and liabilities, having access to liquid assets, such as cash or highly liquid securities, becomes crucial for meeting financial obligations and operational requirements (Beck et al., 2022). Liquidity, in this context, refers to the ease and speed with which an asset can be converted into cash without incurring significant losses in value (Gallagher and Andrew, 2003; Tracy and Tracy, 2014; Vernimmen et al., 2022).

Having sufficient liquidity is extremely important for firms to cover their short-term payment obligations, handle unexpected expenses, manage working capital, and effectively respond to changes in market conditions. The presence of enough liquidity enables market participants to engage in asset buying and selling with efficiency, thereby facilitating price discovery and ensuring smooth market functioning. On the other hand, a lack of liquidity can lead to market illiquidity, increased price volatility, and potential crises (Erel et al., 2021; Jordà et al., 2021). In financial market's transactions and network economic activities, which involve interdependencies and time-sensitive commitments between economic agents, any delays in payment settlements or disruptions in the flow of liquidity can have cascading effects (Gatti et al., 2009; Acemoglu et al., 2012; Carvalho, 2014). These effects can manifest as liquidity problems, credit risks, and systemic issues within a network economy, where firms trade and interact with one another (Acemoglu et al., 2015, 2017; Altinoglu, 2021).

The consequences of not having enough liquidity were evident during the global financial crisis of 2008, where the insufficient availability of liquidity played a significant role in triggering financial distress, credit crunches, and disruptive market conditions. This crisis serves as a strong example of how the absence of sufficient liquidity can have severe consequences for the

financial system and the broader economy (Gorton, 2008, 2009; Lou and Sadka, 2011). Since the 2008 GFC, numerous studies have demonstrated a strong correlation between liquidity and business cycles (Bernanke and Blinder, 1988; Krishnamurthy, 2010; Bigio, 2015; Adrian et al., 2017). Several research attempt to explain the origins of liquidity by closely examining the primary elements and components contributing to economic instability. These studies believe that liquidity arises from the behavior and interactions among market participants and financial intermediaries (Chung and Chuwonganant, 2014). Therefore, understanding the dynamics of liquidity in financial markets is essential for promoting financial stability, reducing the likelihood of liquidity-driven crises, and supporting the overall health and resilience of the economy (Langley, 2014; Thakor, 2015; Jordà et al., 2021).

This study similarly attempts to assess the origins of aggregate fluctuations in a network economy that can arise from *liquidity shortage* and corresponding forces.[1] The contribution of this research to the literature is mainly twofold. First, this chapter investigates which shocks drive cyclical fluctuations from the liquidity components of a network economy and addresses the question "how does the economy respond to liquidity-related variables' shock?". This study distinguishes itself from other similar studies, such as Acemoglu et al. (2012) and Altinoglu (2021), by extracting all short-term elements of balance sheet data, rather than exclusively focusing on receivables and payables. It encompasses current assets and current liabilities of the top 100 U.S. firms, breaking down the associated liquidity elements of the balance sheet into two categories: quick ratio and network measure. These two variables aim to depict the liquidity status of a firm in the broader economy. Furthermore, the study traces how liquidity-related variables such as the quick ratio, network measures, repo rate, and GDP influence and propagate through the system, affecting other interconnected variables within the model. Secondly, this chapter aims to address the question, "What is the contribution of each shock to the business cycle?". The study achieves this by decomposing the variance of the forecast error into the contribution of each variable, explaining the significance of each variable's shock

[1]This chapter henceforth uses the terms "fluctuation", "cyclical fluctuation", "business cycle", and "cycle" interchangeably.

within our system of equations. To the best of the authors' knowledge, this is the first study examining all the short-term elements of the balance sheet and reporting the proportion of each shock within this set of variables.

For this purpose, this study considers a network economy in which firms hold part of the short-term assets to pay for their current debt i.e. the goods, labor, and investments, and then exchange the other part of their internal short-term resources (i.e. the account receivables and payables) to trade intermediate goods. Firms are also able to enter the money market to borrow additional resources to pay off their debts or to purchase their inputs.[2] In such an economy, the inability of firms to meet their short-term liabilities can generate financial and monetary shocks not only to the firm's internal resources but also to the linkages between firms.

Our analysis has shed light on the cascading effects that liquidity disruptions and corresponding forces can have within a network economy. This study uses the Structural Vector Autoregression (SVAR) model to analyze liquidity dynamics in the U.S. economy.[3] The SVAR model is a powerful framework in macroeconomic research to analyze the interactions between different variables, and the joint dynamics of multiple variables in a system and estimate the effects of unexpected exogenous shocks on the variables under study.

This chapter aims to investigate the dynamic components of liquidity movements in a network economy, where firms trade with each other and have short-term assets and liabilities. To do this, the quarterly liquidity data are initially directly derived from the balance sheets of the top 100 big U.S. firms using $S\&P100$ index during the years 2006 to 2020. The sectoral network and liquidity ratio are constructed for the core sectors in the U.S. economy. The interest rate and the Gross Domestic Production (GDP) are also applied to capture the monetary effects

[2]Note that non-financial firms typically do not access funding directly from money markets; instead, they rely on financial intermediaries for financing. However, this study examines these dynamics to elucidate the impact of firms' liquidity shortages on the money market and consequently, on interest rates. The effect of firms obtaining financing through financial intermediaries can be indirectly captured by network measures, which reflect trade activities among firms (see Altinoglu (2021) for a similar argument).

[3]The term "structural" in structural VAR addresses the assumption that the relationships between the variables are based on the underlying economic structure and can be applied to identify the sources of the innovations.

and output effects in the economy. We also found it desirable to improve the accuracy of results by adding the exogenous variables Federal Funds Rate (FFR), Consumer Price Index (CPI), money supply, and the U.S. dollar exchange rate, which are important drivers of liquidity in the economy. The cyclical components of the variables are then extracted by Hodrick–Prescott (HP) filter and applied to the SVAR model to capture the business fluctuations arising from the liquidity movements.[4] The research identifies the relevant innovations of the variables of interest and describes the responses of the system to each structural shock by analyzing the propagation mechanism of shocks through the Impulse Response Function (IRF). This research also investigates the importance of each innovation by reporting the proportion of each shock throughout the whole system by decomposing the Forecast Error Variance (FEV).

Overall, this chapter highlights the importance of liquidity in financial markets, emphasizing the need for firms to have access to sufficient liquid resources to ensure smooth operations, fulfill financial obligations, and promote overall financial stability. By studying the dynamics of liquidity, policymakers, regulators, and market participants can enhance their understanding of the factors that influence liquidity conditions, develop appropriate measures to manage liquidity risks, and establish robust frameworks that mitigate the negative effects of liquidity shortages. The chapter structure plans as follows; Section 4.2 explains the related literature about the liquidity issues and aggregate fluctuations as well as the background about the SVAR model and the approaches for the identifications of the model. In Section 4.3 the description of the applied variables and the SVAR model setup are elaborated. The empirical results are explained in Section 4.4 and, finally, the findings are summarized in Concluding Remarks.

[4] Hodrick and Prescott (1997) filter or HP decomposition is a popular tool in macroeconomics to study business cycles or fluctuations by decomposing the time series variables into the trend component and cycle component. The details are explained in Section 4.3.1 and Appendix B.2.

4.2 Related Literature

The related literature of the chapter is mainly covered in two parts. The first part explains the studies around liquidity issues and business cycles, and the second subsection elaborates on the Structural Vector Autoregression (SVAR) models and different approaches of identification.

4.2.1 Liquidity and Business Cycles

The concept and the level of liquidity is crucial for the entire economy as it is strictly associated with the ability to meet short-term obligations and respond to unexpected events (Gallagher and Andrew, 2003). Business cycles and market volatility are strictly related to liquidity, and the interaction of the two has been the topic of interest in macro-finance research in the economy (Krishnamurthy, 2010; Bigio, 2015; Adrian et al., 2017). In monetary economics and macroeconomics, liquidity addresses to the availability and accessibility of money or cash in an economy and its effect on economic determinants including inflation, spending, investment, etc. Liquidity in this context is defined by the ease with which money is used for trades and transactions as well as for the response of the monetary system to changes in demand for money in the economy and can be measured by the volume or amount of money in circulation (Tracy and Tracy, 2014; Vernimmen et al., 2022).

There is a lot of research on the origins of liquidity issues from different points of view. One line of literature discusses the level of liquidity based on the types of financial assets in the market including bonds and stocks, commodities, real estate etc. There are studies that have focused mainly on stock liquidity (Brogaard et al., 2017; Naik and Reddy, 2021), some studies discuss bond liquidity and its role in financial crises (Chen et al., 2007; Dick-Nielsen et al., 2012), and some focus only on commodity volatility and its returns on market liquidity and liquidity risk (Zhang and Ding, 2018; Zhang et al., 2019). He et al. (2018) also developed

a model to investigate the connection between asset liquidity and market volatility in the real estate market.

Another strand of the literature studies the market structure in the provision of liquidity. They argue how liquidity arises from the behavior and interactions of market participants and financial intermediaries (Chung and Chuwonganant, 2014). Gorton (2008), Gorton (2009), and Cetorelli et al. (2012) for instance are limited to the role of financial intermediaries in providing liquidity and also for their potential systemic disruption. Lyons (1995) and Krishnamurthy (2010) have also pursued to investigate the underlying mechanisms and channels that drive the provision and demand of liquidity including trading costs, information asymmetry, and market volatility. Understanding the origins of liquidity is essential for clarifying how liquidity is influenced by different factors and how it affects market outcomes.

Other studies have expanded on studying micro-level mechanisms and micro-foundations of driving liquidity supply and demand. Lyons (1995) assesses the structure of the market in providing liquidity to the foreign exchange market. They find the significant role of asymmetric information and the effectiveness of market interventions in market volatility and market failures in the foreign exchange market. The paper also explains the market players are willing to supply liquidity under the conditions in which the cost and the price movement volatility of liquidity provision are low. Tyagi (2000) also designs a liquidity provision model in loan markets and sheds light on how the banking system evaluates the benefits and costs of supplying liquidity to borrowers.

There is another line of literature that discusses liquidity from a monetary point of view, where the central banks inject money into the economy through financial instruments like different types of interest rates or printing fiat money. Kiyotaki and Moore (2019) discuss the role of government policy on asset prices and liquidity through open-market operations. Jessop (2013) highlight the role of fiat money in lubricating an economy and discuss that the liquidity is generated not from the balance sheet of firms in the economy but from the balance sheet of

central banks. Calvo (2012) also argue the destructive role of CB intervening in the market and printing the fiat money (see also Goodhart (2011) and Brunnermeier and Schnabel (2015)).

The connection between liquidity and the business cycle is also another strand of literature that has substantial implications for the whole health of the economy. The important early study by Bernanke and Blinder (1988) found that liquidity crises can contribute to market volatility and economic recessions. They examine that changes in credit conditions can result in volatility of aggregate demand and output. They also established that the interbank market's frictions can lead to liquidity shortage and spillover throughout the whole economy. Bernanke and Gertler (1986) developed the framework to assess the impact of liquidity shocks and its fluctuations in unemployment, investment, and output. Their finding shows that liquidity shock contributes more to the industries and sectors that depend on external financing and have high levels of debt.

Other studies build upon these works and discuss the micro origins of liquidity and how they associate with the business cycle. They mainly discuss the role of the banking system and financial intermediaries in providing and managing liquidity in the economy. Acharya and Viswanathan (2011) explain the role of financial sectors' regulation and structure in determining the magnitude of liquidity in the economy or in rolling over the liquidity shortage throughout the economy. Financial institutions could hold more liquid assets during times of stress and uncertainty. This liquidity hoarding behavior may aggravate the liquidity stress during economic downturns since they may not be willing or able to provide liquidity to other counterparties. They also suggest that bank leverage may result in moral hazard and thus liquidity shortage. Cetorelli and Peristiani (2012) and Cetorelli et al. (2012) similarly examine the contribution of liquidity in the banking system during the Great Financial Crisis (GFC) in 2007-8. They illustrate that banks experience higher losses once they save lower amounts of liquidity during the financial crisis and this can again lead to less lending. The decline in lending then can play a negative role on the whole economy and thereby trigger the recession. Some studies focus on the role of financial intermediaries' capital structure and liquidity provision in business

cycles (Begenau, 2020; Jordà et al., 2021). Some also analyze the microstructure of markets to determine market prices or the behavior or the role of market participants on the business fluctuations (Bernanke and Gertler, 1986; Li et al., 2021).

This chapter contributes to the strand of the literature that investigates the origins of shocks to the business cycle. A growing literature examines the contribution of shocks to aggregate fluctuations, building upon foundational work of Cochrane (1994) and progressing with Gabaix (2011), Foerster et al. (2011), Acemoglu et al. (2012), Stella (2015), Atalay (2017), and Altinoglu (2021). Acemoglu et al. (2012) and Bigio et al. (2016) demonstrate how the network structure within an economy can drive fluctuations from idiosyncratic, firm-level shocks using an input-output model. Altinoglu (2021) similarly models a network economy to understand the mechanism of fluctuations. However, it is restricted to the type of shock to the economy and addresses the importance of financial shock in the fluctuation, and he does not explain the dynamic of shock in the network. Overall, the literature shows constant attempts to understand the origins of fluctuation in the economy. This chapter contributes to the literature by explaining the essential role of liquidity and its profound impact on economic business cycles. However, further exploration in this area is required to enhance how policymakers can better control economic volatility.

4.2.2 Structural VAR Model

The Structural Vector Autoregression (SVAR) model is widely used in macroeconomics and econometrics to analyze the relationships between economic variables. The SVAR model was first introduced by Christopher Sims in his 1980 paper, "Macroeconomics and Reality" (Sims, 1980a,b). Sims formulated a new macroeconomic model as a way to analyze the relationships between variables such as inflation, unemployment, and output in order to study the business cycle (Sims et al., 1986). Sims (1980a,b) suggest the SVAR tool as an alternative identification approach to analyse macro-model and overcome the false identification in macroeconomics.

Bernanke (1986) and Shapiro and Watson (1988) developed a new class of SVAR econometric models to argue the business cycle and the relationship between money and income in the financial market. They focus more on the identification of the errors of the system that are taken as an exogenous shock, rather than identifying only the (autoregressive) coefficients.

After Sims (1980a,b) introduced the model, many studies used the model to address the business cycles in an economy and assess the dynamics of shocks. Some of the recent papers that apply the SVAR with the focus on liquidity and market interactions are da Silva Souza and Fry-McKibbin (2021), Múnera and Agudelo (2022) and Doojav et al. (2023). We also apply the SVAR model as one of the major means of extracting and analyzing information about the macroeconomy in order to quantify impulse responses of macroeconomic shocks (innovations) as well as investigate the contribution of different shocks to business cycles and forecast errors through decompositions of variance. To draw this information, first, a reduced form VAR model is fitted to summarize the data and then a SVAR model is carried out to interpret the data, where the errors of structural equations are taken as the economic shocks, and the parameters of these equations are estimated by restoring the information from the VAR representation. However, for any block of structural equations, recovering and estimating the structural equation shocks and parameters requires identifying restrictions in order to reduce the number of "free" parameters in the structural equations to the number that can be estimated and recovered from the data in the reduced form.

The identification issue is a crucial step in estimating the structural parameters of SVAR models and has been a topic of debate in the literature. There are different approaches for identifying the structural shocks in SVAR models, including long-run restrictions, sign restrictions, Cholesky identification, proxy variables, and external instruments. There is a strand of SVAR literature that focuses on different approaches of specifying the restrictions to perform an appropriate identification. Lütkepohl (2005), Ouliaris et al. (2016), and Kilian and Lütkepohl (2017) illustrate the steps to perform SVAR model and explain different types of identification to restrict the parameters with the focus on the AB model and sign restrictions.

Gottschalk (2001) and Buckle et al. (2002) also assess different types of identification and address issues in imposing the restrictions. According to the literature, since we are focusing on the business cycle and short-term fluctuations, it is appropriate to use short-term identification methods such as the AB model and Cholesky identification rather than the long-term model, Vector Error Correction Model (VECM). This is not necessary and may be even obscure as it is possible that imposing long-term restrictions leads to unreliable results for investigating the business cycle. Sign restrictions involve imposing economic theory-based restrictions on the sign of the impulse response functions, while proxy variables and external instruments use exogenous variables to identify the structural shocks. There are also several advantages to proxy variables or external instruments such as limited validity, weak instruments, etc (Ouliaris et al., 2016).

To the best of our knowledge, there seems to be no recommendation on any specific approach, and some apply a mixed set of restrictions or a combination of the methods that are described above. However, overall in practice, without a particular context, any of the approaches can be employed depending on the preferences of the researcher and the context of the research. Sims (1980b) also discusses that "structural identification is not ordinarily needed and that false restrictions may not hurt." Among all the identification methods, we apply the Cholesky decomposition method as it is considered a good and reliable method for identifying structural shocks in SVAR models despite all the shortcomings (Lütkepohl, 2005). The Cholesky decomposition imposes a recursive structure on the model based on their economic theory which involves ordering the variables in the system. This approach assumes that the innovations propagate through the system in some specific order that is consistent with economic theory. Several research has shown that the Cholesky method leads to more accurate and robust results compared to other identification methods. Further, Kilian and Lütkepohl (2017) shows that the Cholesky identification method outperformed other approaches in a macroeconomic model in terms of accuracy and robustness. Furthermore, it is sufficient to implement and provide meaningful interpretable results.

4.3 Data and Empirical Model

This section attempts to explain two parts of the chapter. Subsection 4.3.1 describes the data and illustrates how the choice of variables including the endogenous and exogenous variables are selected. We also explain how we build a network that shows the flow of funds between each industry. Subsection 4.3.2 shows how the SVAR model is applied to investigate shocks driving cyclical fluctuations in the economy. The structural VAR is applied to address the questions "How does the economy respond to liquidity-related variables' shock?", and "What is the contribution of each shock to the business cycle?" (Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

4.3.1 Data Discription and Choice of Variables

We attempt to collect the data associated with the liquidity issue. The data we use are mainly two categories; endogenous variables and exogenous variables. The endogenous variables are mainly three types; Firm balance-sheet data (i.e. quick ratio and network data), interest rate (i.e., repo rate), and the output growth of US industrial production industries. The balance sheets of top big firms in the U.S. are used to capture the exchange of the current assets and current liabilities between firms. By applying the interest rate data we investigate the effect of pricing of the money in the economy and the effects of borrowing-lending spillovers in the money market. The total output of the economy also shows the overall effect of liquidity in the financial market and money market on the economy as a whole. In this subsection, we elaborate on the applied data and the reasons behind the choice of these variables. We also include the federal funds rate, money supply, inflation, and the dollar exchange rate as exogenous variables to improve the results. We explain the details of each variable below, and Table B.2 in Appendix B provides some descriptive statistics about all the applied variables.

1. Firm balance-sheet data. Since we are planning to examine how easily firms' assets can be converted into cash or other liquid assets without any devaluation in order to pay off their liabilities, we are looking at the liquidity ratio, which reflects how a firm can function if a company can pay off its creditors from their total available cash or liquid assets.[5] To look closely into how liquidity flows in the economy, the liquidity data are directly derived from balance-sheet of the top 100 big firms which is collected according to $S\&P100$ index during the years $2006Q1$ to $2020Q4$.[6]

To discuss the liquidity we shall look at both sides of the balance sheet i.e. the current assets and current liabilities as the most common liquidity ratio formula suggests. However, since we intend to investigate closely the micro origins of fluctuations, the short-term assets and short-term liabilities are then decomposed into two parts; the network effect and the liquidity ratio. The network effects comprise the account receivables and account payables, and the liquidity ratio measures a company's ability to pay off its current liabilities (i.e., payable) with its total current assets by the following formula,

$$LR = \frac{CA}{CL} \tag{4.1}$$

where LR denotes the liquidity ratio, CA is the current assets, and CL is the current liabilities. More specifically, we use the concept of quick ratio in Equation 4.1 as one of the most important liquidity ratios to decompose the elements of a balance sheet;[7]

$$QR = \frac{C + CI + S + AR}{CL} \tag{4.2}$$

[5]There are several measures and liquidity ratios that have been constructed to assess a firm's maturity mismatch such as current ratio, quick ratio, cash ratio, etc. In this study, we focus on the current ratio and quick ratio to assess the ability of firms in short-term payments (see more details in Vernimmen et al. (2022)).

[6]The data are collected from the Datastream dataset. The list of the firms will be available upon request.

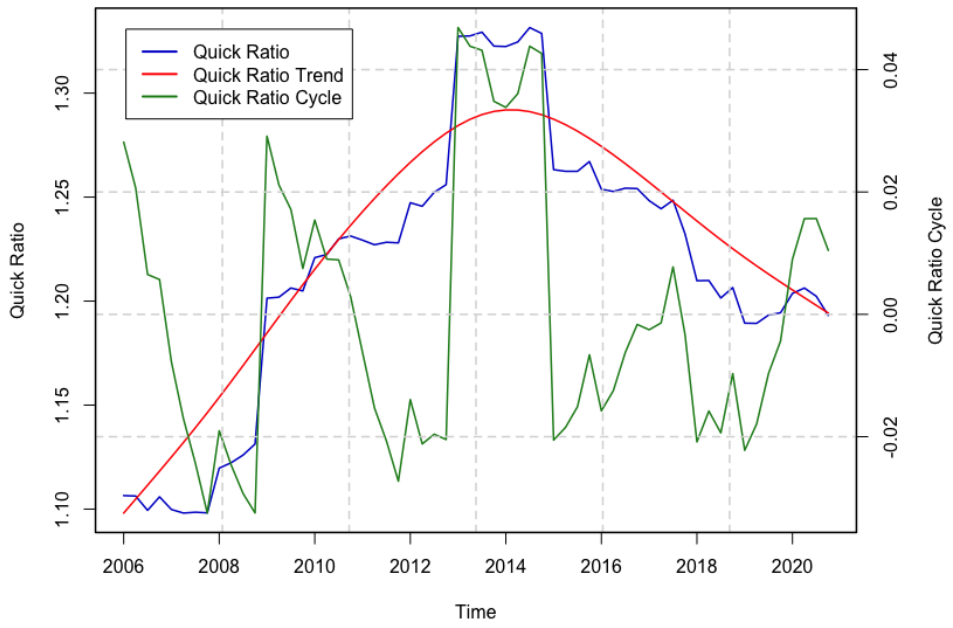
[7]There are several different liquidity ratios available depending on the purpose to evaluate the status of the debtor; current ratio, quick ratio (i.e., acid test ratio), operation cash flow ratio, working capital, working capital ratio, and absolute liquid ratio (see Vernimmen et al. (2022) for the details of each ratio). The quick ratio is chosen over other ratios as Madushanka and Jathurika (2018) shows the significant role of quick ratio in firms' performance compared to other liquidity ratios.

Where QR denotes quick ratio, C is cash and its equivalents, CI is a current or short-term investment, S is marketable securities, AR is accounts receivable and CL is current liabilities. CL are short-term obligations that a firm is expected to settle within the current accounting period. For this study, the elements of current liabilities mainly include Account Payable (AP) and other current liabilities (such as wages payable, operating costs payable, short-term loans, taxes, accrued liabilities, dividends payable, etc.). We then isolate accounts receivable (AR) and accounts payable (AP) to construct the network effect, and the remaining elements capture another vital aspect of liquidity to discuss the liquidity dynamic (henceforth, for ease of reference and to simplify the discussion, we adopt the term 'quick ratio' to denote this residual liquidity measure).[8] Figure 4.1 plots the quick ratio as well as its corresponding trend and cycle components. The trend and cycle are calculated by the Hodrick–Prescott (HP) filter (see the details in Appendix B.2).[9]

[8]We assume that other components of the balance sheet stay fixed and there is no minimum capital requirement as there are no constraints for non-bank and non-financial firms from the regulatory end (the Basell III). Non-financial firms in the US economy are not required to hold a minimum amount of capital. However, all firms need to maintain a sufficient level of financial resources to meet their financial obligations and continue to operate. This can include holding adequate cash reserves, maintaining a healthy debt-to-equity ratio, and having access to credit or other sources of financing.

[9]Hodrick and Prescott (1997) filter or HP decomposition is a popular tool in macroeconomics to study business cycles or fluctuation by decomposing the time series variables into the trend component and cycle component. In this paper, the cycle component is used in the model as the model requires the stationarity of the variables.

FIGURE 4.1: Time Series of Quick Ratio



Note: Figure depicts the time series of endogenous variable quick ratio used in the model. The Figure plots the quick ratio and its corresponding trend and cyclical components that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis is the scale of the quick ratio, and the left vertical axis represents the scale of the cyclical component of the quick ratio. The horizontal axis shows the yearly time period.

Data source: Calculated and plotted by the author using Datastream database.

2. Financial Network. We aim to capture the network effects and interconnections among firms within the economy. The initial step to constructing the network for each period involves accessing disaggregated data on liquidity flows. To achieve this, we collect quarterly *liquidity-related balance sheet data* for the top 100 large firms from the Datastream database spanning from 2006$Q1$ to 2020$Q4$. The balance sheet elements encompass current assets and current liabilities, as explained earlier. For network construction, we utilize the elements of Accounts Receivable (AR) and Accounts Payable (AP) to develop a proxy for the financial network connecting firms.

Calibrating the input and output of firms requires data on fund flows between firms, which unfortunately is not available. To address this, we create a proxy for trade flows at aggregate levels among industries by leveraging industry-level input-output data from the Bureau of Economic Analysis (BEA) and firm-level balance sheet data from the Datastream dataset. The

BEA database offers annual trade flows between industry pairs. As a response to the limited availability of liability breakdowns for individual counterparties, we aggregate the liquidity data at the industry level. This approach allows us to exploit the industry-by-industry input-output table from the BEA, facilitating the breakdown of liabilities and enabling us to investigate the extent of liabilities between industries.[10]

Our model considers an environment with $N = 10$ industries in which the industries interact with each other by creating obligations from their suppliers. To analyze the network effect of an economy, we first construct the proxy matrix X of our financial network by a finite pair of set (N, E) using the balance-sheet firm-level data, where N is the nodes and E is the set of edges. In our network, the nodes are the top 10 big sectors and the edges represent flows of claims or the obligations of each firm to its counterparties. More precisely, our model considers an economy with N sectors, where each sector i holds the liabilities of its counterparties. Every financial linkage x_{ij} denotes the liabilities of i to j at every period for any $i, j \in \mathcal{N} = \{1, ..., N\}$. x_{ij} corresponds to accounts receivable in the liability side of the balance sheet of a firm. Thus, the pattern of liability holding for the firms across the economy at every period can be shown in the following form:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NN} \end{pmatrix}$$

These edges or linkages indicate the flow of claims to each sector, i.e. x_{ij} is the net amount that industry i owes to industry j. We then compute *net receivables* of a firm by $X^n = X^R - X^P$,

[10] Main industries we use for this study are as follows: Utilities, Manufacturing, Wholesale, Retail trade, Transportation, Information, Finance; insurance; real estate; rental; and leasing, Professional and business services, Educational services; health care; and social assistance, Arts; entertainment; recreation; accommodation; and food services.

where X^R is the receivable network, and X^P is the payable network and X^n is the net receivable with all the elements $x_{ij}^n \geq 0$.

After constructing the financial network, we try to use different types of network analysis tools and metrics to gain a more complete understanding of the risk profile of a financial network. However, it is important to note that the volatility of a system can arise from a variety of sources and different types of shocks such as changes in market conditions, economic events, and shocks to individual nodes or groups of nodes. Additionally, although there are several network statistics that can provide useful insights into the risk of a financial network, none of them can provide a single network measure that can fully capture the volatility of a financial network since the risk of a financial network is a complex and multifaceted concept, and it highly depends on a range of factors such as network structure and topology, the level of interconnectedness, and the quality of the assets, liabilities, and one single metric cannot fully capture its complexity (Albert and Barabási, 2002; Gao et al., 2017).

Therefore, we use different metrics as well as a combination of metrics to overcome the complexity issue, to capture the whole network effects, and to assess the susceptibility of financial networks to volatility and risk. The first type of network measure that we use is the first two moments of degree distribution (i.e., mean and variance), and the second part is our proposed network index that is built using two network centralities:

i. Moments of degree distribution: Network analysis methods allow us to investigate the volatility and risk of the financial network as they provide a powerful framework to visualize and analyze the structure and dynamics of the system. The moments of a degree distribution give summary statistics that show the aspects of the distribution. The degree distribution is one of the network measures that provide insights into the volatility of financial networks (Jackson, 2010; Gai and Kapadia, 2010). The degree distribution describes the distribution of the number of linkages or connections that each node has and it can identify how evenly or unevenly connected the nodes in the network are. A network with a large mean or high

variance in degree distribution may contribute more to volatility since just small changes in the connectivity or linkages of a few key nodes may have a disproportionate and destructive impact on the overall structure of a network.

We use the first two moments of the degree distribution which can give us insight into different aspects of the network's topology and potential systemic risks. The first moment, *mean degree*, denotes the average number of connections for each node in the network. A larger mean in the context of financial networks represents a larger interconnectivity between the sectors or industries that can lead to contagion and systemic risk if one industry fails. Another moment of the degree distribution is the variance of degree. This moment measures the level of variability in the number of connections that each node has. A high variance of degree can imply that there are a small number of nodes with a very high level of connectivity. This can make the network more susceptible to the failure of systemically important nodes.

As these moments are restricted to the number of edges, they may not be so helpful as the volume of the edge matters. We then use the weighted moments of degree distribution. The weighted degree distribution of a directed network X provides the probability distribution of the total weights of all edges (incoming or outgoing) for each node i in the network. The weight here refers to the size of receivables associated with each node or industry in the network.[11] The mean and variance of degree here are different from the standard degree distribution since it takes the weights on the linkages between nodes into account. More specifically, the weighted distribution gives the average and variance weight of the edges connected to nodes with a given degree (Qiu et al., 2010). The weighted mean degree of the network is the average total weight of all the linkages/connections for all industries i in the network, where the weighted degree of a node is given:

$$\langle k \rangle_w = \frac{\sum_{i=1}^{N} w_i}{N} \tag{4.3}$$

[11] Battiston et al. (2010) explains the structure of networks in finance and economics using the weighted degree distribution and calls the corresponding quantity as the strength of an edge.

where $\langle k \rangle_w$ is the weighted mean degree of the network, w_i is the weighted degree of node i, and N is the total number of nodes in the network. The network with a larger weighted mean degree shows that the nodes, on average, are connected to each other more strongly. This implies a higher degree of financial interconnectedness in the network. Figure 4.2a plots the mean degree distribution and its corresponding trend and cycle trends of the network.

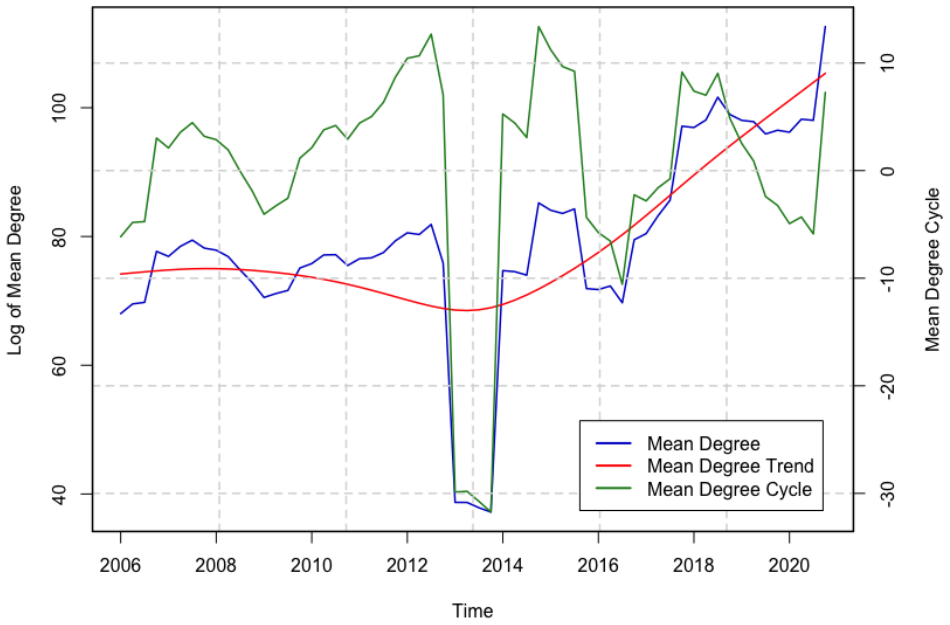
We also apply the *variance* of the weighted mean degree using the following formula:

$$\langle \sigma^2 \rangle_w = \frac{1}{N} \sum_{i=1}^{N} (k_i - \langle k \rangle_w)^2 \tag{4.4}$$

where $\langle \sigma^2 \rangle_w$ denotes the variance of the weighted mean degree, k_i is the weighted degree of node i, N is the total number of nodes, $\langle k \rangle_w$ is the weighted mean degree of the network. The variance of the weighted mean degrees can also provide some information about the structure of the network. A high variance explains that a few nodes (i.e., industries) have high-weighted degrees and dominate in the network while the majority of nodes are connected with low-weighted degrees. However, a low variance declares that the weighted degrees of nodes are relatively distributed more evenly across the network. Figure 4.2b shows the variance degree and its corresponding trend and cycle trends of the network.

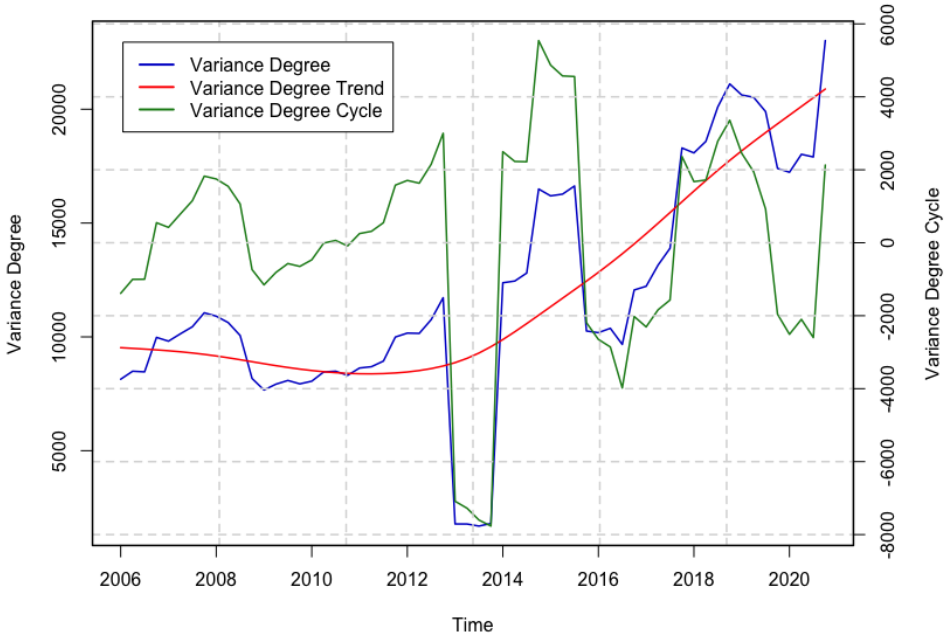
FIGURE 4.2: Weighted Degree Distribution

(A) Mean Degree



Note: Figure depicts the time series of endogenous variable mean degree distribution used in the model. The Figure plots the mean degree distribution and its corresponding trend and cyclical components that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis is the scale of the mean degree distribution, and the left vertical axis represents the scale of the cyclical component of the mean degree distribution. The horizontal axis shows the yearly time period.

(B) Variance Degree



Note: Figure depicts the time series of endogenous variable variance degree distribution used in the model. The Figure plots the variance degree distribution and its corresponding trend and cyclical components that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis is the scale of the variance degree distribution, and the left vertical axis represents the scale of the cyclical component of the variance degree distribution. The horizontal axis shows the yearly time period.

Data source: Calculated and plotted by the author using the Datastream database.

ii. Network index: Although several network statistics can provide useful insights into the risk of a financial network, none of them can provide a single network measure that can fully capture the volatility of a financial network (Albert and Barabási, 2002). Therefore, we use a combination of different centrality measures to overcome the complexity issue and capture the whole network effects so as to assess the susceptibility of financial networks to volatility and risk. Centrality measures are very common and popular in network analysis to identify the most important nodes and linkages in a network (Jackson, 2010). Several centralities are applied in conjunction with other metrics and analyses to fully capture the network's risk profile. We use different combinations of centrality measures may be used to address different research questions or to explore different aspects of network structure and function.

We propose a new index to capture the network effects of financial flows using the product of Katz centrality and edge betweenness centrality in order to identify nodes that are important for their overall influence within the network (captured by Katz centrality) and their potential to control the flow of transactions (as measured by edge betweenness centrality) (Katz, 1953; Freeman, 1977; Freeman et al., 2002; Brandes, 2008).[12] Our index actually identifies key nodes/intermediaries in a network that are both influential and have the potential to act as gatekeepers for transaction flow. This measure tries to capture the effect of key nodes in the network which serve as both hubs and bridges between industries, so it can be helpful in understanding the potential impact that changes to individual nodes/links or groups of nodes may have on the overall structure and stability of the network (Chan-Lau, 2018).[13]

We use average network centralities to obtain the average influence of nodes in a network as a single metric to have a proxy of the whole network and can provide useful insights into the risk of a financial network. The average of all nodes can help identify which nodes are the most important or influential in the network, and thus which nodes may pose the greatest risk

[12]Katz centrality and Google's PageRank are variants of the eigenvector centrality. The advantage of Katz centrality compared to the other two centralities is that it not only takes the influence of immediate neighbors into account, but it considers the distant neighbors using the factor α.

[13]The product of network centralities is often used in studies that are interested in identifying different aspects of nodes or linkages. The details of each centrality are explained in Appendix B.1.

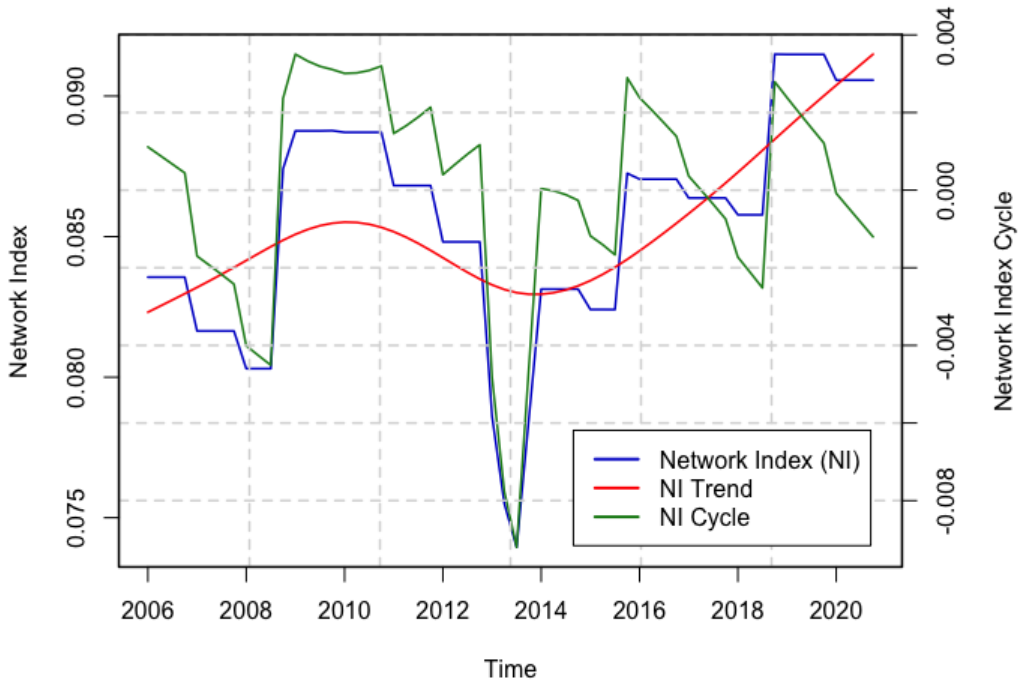
if they were to fail or experience distress.[14] The measure shows how strongly the influence of each node on average is affected (amplified or diminished) by the influence of other nodes, and thus how a shock to one node may ripple through the network (Thurner and Poledna, 2013; Huang and Wang, 2018; Cao et al., 2022).

$$\underbrace{n^{-1}\sum_{i=1}^{n} c_K(i) \times n^{-1}\sum_{s,t\in V}\frac{\sigma(s,t|i)}{\sigma(s,t)}}_{c_T(i)} = \beta\underbrace{n^{-1}\sum_{i=1}^{n} c_K(i)}_{c_K(i)} + \gamma\underbrace{n^{-1}\sum_{s,t\in V}\frac{\sigma(s,t|i)}{\sigma(s,t)}}_{c_B(i)} + \epsilon_N \tag{4.5}$$

where $\overline{c_K(i)}$ in the right-hand side denotes average Katz centrality and represents the nodes' effect and $\overline{c_B(i)}$ is the average edge betweenness centrality and captures the linkages effect (The definitions and details for each centrality are explained in Appendix B.1). The estimated $\hat{\gamma}\overline{c_B(i)}$ then can reflect the 'pure' linkage effect and the estimated $\hat{\beta}c_K(i)$ can capture the pure node effect. Since a network is a complex system and there may be a common effect from both $\overline{c_K(i)}$ and $\overline{c_B(i)}$, ϵ_N actually captures the common effect. We use the fitted value of the product of Katz and edge betweenness centrality, $\widehat{c_T(i)}$, to capture both the linkage effect and node effect. In this study, $\hat{\gamma}\overline{c_B(i)}$ can help to identify debt relationships that are important in connecting different groups or clusters of sectors in the network and $\hat{\beta}\overline{c_K(i)}$ can capture the important sectors in transmitting the debt. More details as well as information about $\hat{\gamma}$ and $\hat{\beta}$ can be found in Table B.1 in Appendix B.1.

[14] In the literature, we discussed one of the main limitations of SVAR model that is by adding more endogenous variables to model, more restrictions required for the identification of the model. Therefore, we avoid using local centralities which report a measure for each node. Instead, we focus on global metrics that provide a single measure for the whole network.

FIGURE 4.3: Time series of the Network Index



Note: Figure depicts the time series of the endogenous variable network index used in the model. The Figure plots the network index and its corresponding trend and cyclical components that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis is the scale of the network index, and the left vertical axis represents the scale of the cyclical component of the network index. The horizontal axis shows the yearly time period.

Data source: Calculated and plotted by the author using the Datastream and the BEA datasets.

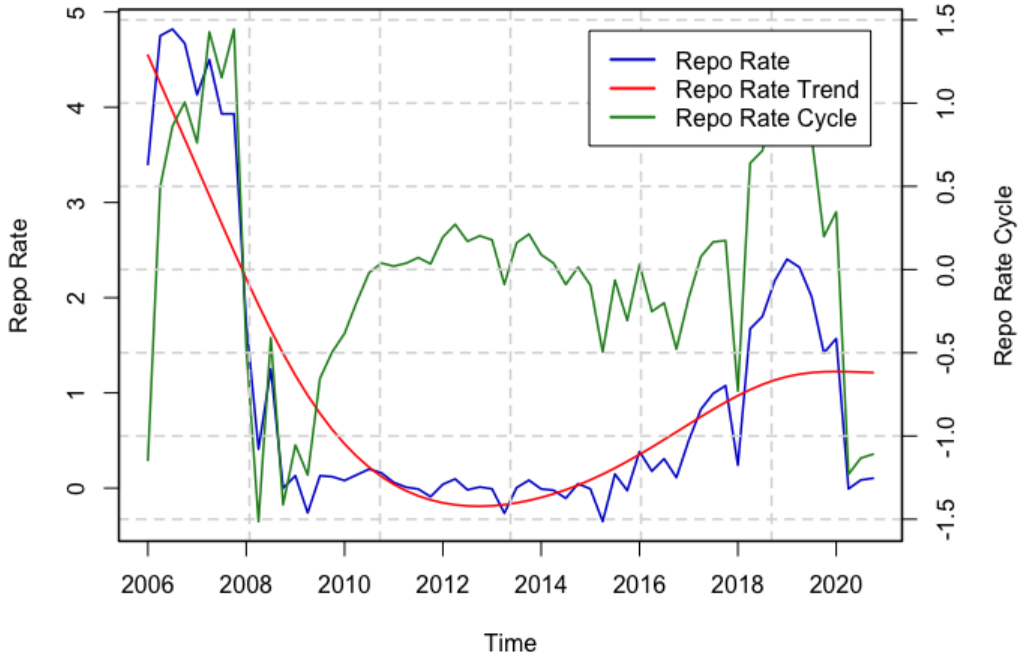
However, it is important to note that the volatility of a financial network is a complex and dynamic phenomenon that can depend on a range of factors beyond network structure and topology. Therefore, it is important to use network measures in combination with other analytical tools and to consider the specific context and characteristics of the network in question.

3. Repo rate. The *Repurchase Agreement (Repo) rate* is another variable that we need to take into account as it captures monetary shock in our system of economy. The repo rate is the interest rate that is concerned with liquidity as financial institutions can borrow and lend short-term funds in the money market. The Repo rate is endogenously determined by supply and demand in the money market and fluctuates throughout the day based on the availability

of funds in the market and the demand for short-term financing by institutions (Nath, 2015; Fuhrer, 2018; Kozlowski and Jordan-Wood, 2022).

We collect the quarterly repo rate for the sample time span from FRED. Figure 4.4 shows the quarterly time series of interest rate, its trend and cyclical movement in the US economy from 2006 to 2021.[15]

FIGURE 4.4: Time Series of Repo Rate



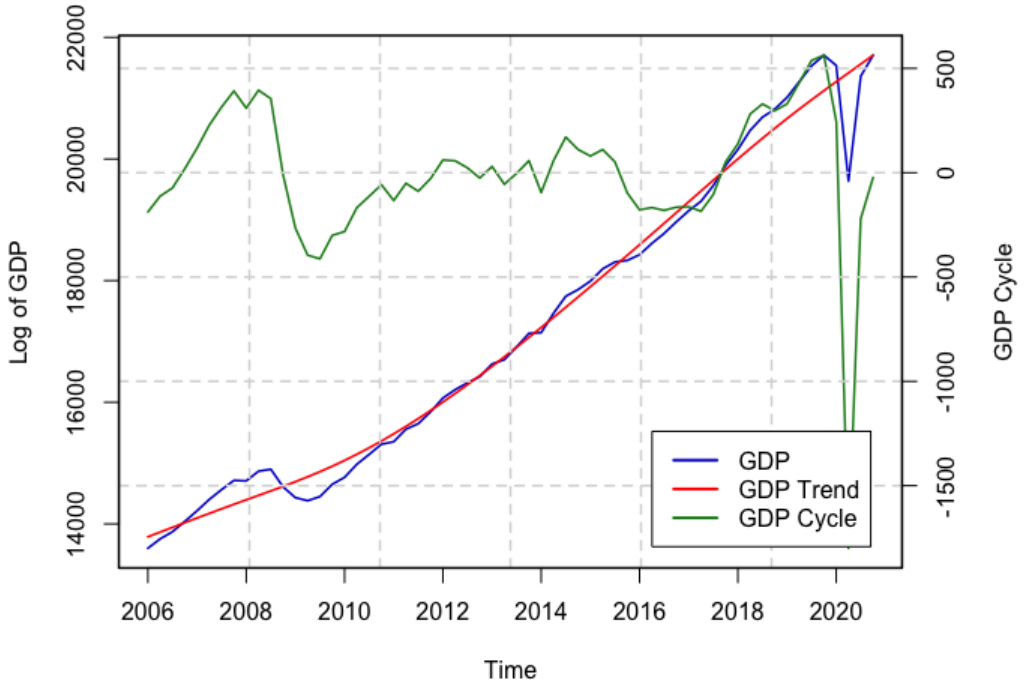
Note: Figure depicts the time series of the endogenous variable repo rate used in the model. The Figure plots the repo rate and its corresponding trend and cyclical components that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis is the scale of the repo rate, and the left vertical axis represents the scale of the cyclical component of the repo rate. The horizontal axis shows the yearly time period.

Data source: Calculated and plotted by the author using the Datastream.

[15] We have three different types of interest rate. Similarly, the Secured Overnight Financing Rate (SOFR) is a benchmark interest rate to reflect the cost of borrowing money in the short-term funding markets. SOFR is a broad-based benchmark rate that is based on transactions in the repo market, specifically overnight loans collateralized by U.S. Treasury securities. However, the Repo rate is a more specific interest rate that reflects the cost of borrowing and lending cash in exchange for high-quality collateral such as U.S. Treasury securities or other types of securities. SOFR is calculated as a volume-weighted median of overnight Treasury repo transactions, while the Repo rate is determined by supply and demand in the repo market, where market participants negotiate borrowing rates based on the specific collateral being used and the perceived creditworthiness of the borrower. The SOFR may slightly be a better indicator of short-term funding costs as it covers a wider range of financial products. The reason we apply the repo rate over the SOFR is because of the availability of historical data. SOFR was introduced for the first time by the Federal Reserve Bank of New York in April 2018, while the repo rate has been available for a longer period of time, with the year going back to 2000.

4. Gross Domestic Production (GDP). We finally need to apply the *Gross Domestic Production (GDP)* to analyze the effect of liquidity and interest rate on the real output aggregate fluctuation and volatility (Bigio et al., 2016; Altinoglu, 2021). Figure 4.5 plots the quarterly time series of GDP and its corresponding trend and cycle components of the US economy from 2006 to 2021.

FIGURE 4.5: Time series of GDP



Note: Figure depicts the time series of the endogenous variable GDP used in the model. The Figure plots the GDP and its corresponding trend and cyclical components that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis is the scale of the GDP, and the left vertical axis represents the scale of the cyclical component of the GDP. The horizontal axis shows the yearly time period.

Data source: Calculated and plotted by the author using the FRED.

Exogenous variables. We found it desirable to include further exogenous variables in order to have more accurate results. The role of federal funds rates, money supply, consumer price index (CPI), and dollar exchange rates on liquidity and business cycles, and how policymakers can leverage these relationships to maintain economic stability have been a topic of interest for researchers and policymakers for decades. These variables and their interactions are expected to fundamentally impact the business cycle and macroeconomic outcomes, influencing the cost

of borrowing and the availability of credit. Therefore, the variables are added to the model for the sample period under study. The summary statistics for the exogenous variables of interest can be found in Table B.2.

The *Federal Funds Rate (FFR)* is the interest rate at which banks lend money to each other overnight to meet reserve requirements. Interest rate plays a crucial role in determining the availability of credit and the cost of borrowing, which in turn affects the level of liquidity in the economy. For example, the Federal Reserve lowered interest rates to near zero to boost liquidity in the financial system during the global financial crisis of 2008 and stimulate economic activity. This policy helped to prevent a full-blown economic depression and promoted borrowing (Krishnamurthy and Vissing-Jorgensen, 2011; Altavilla et al., 2022). The FFR is applied as an exogenous variable as it is set by the Federal Reserve and serves as a benchmark for other interest rates in the economy. The federal funds rate has a significant impact on the business cycle, as it influences borrowing and spending decisions by households and businesses. Sims (2013), for example, shows how changes in the Federal funds rate can affect credit and spending and thereby economic activity. The paper also declares how the federal funds rate affects the yield curve, long-term interest rates, and investment decisions.

The *money supply, or base,* is another exogenous variable that refers to the amount of money in circulation in the economy. This includes physical currency, bank deposits, and other liquid assets and is mainly controlled by the central bank. The money supply along with the interest rate has a significant impact on liquidity, as it impacts the availability of credit and the cost of borrowing. For instance, Benigno et al. (2020) study the relationship between monetary policy, bank credit, and liquidity. The study further discusses liquidity trap phenomena, where interest rates are close to zero, and central banks intervene in the market and increase liquidity by using unconventional monetary policy tools such as quantitative easing. Senhadji and Khan (2000) also discusses the role of money supply on liquidity and how the central bank manages the money supply through open market operations, reserve requirements, and discount rates.

The *dollar exchange rate* can also affect the liquidity and economy mainly through two channels. First, the dollar exchange rate has a profound impact on liquidity in the economy as the value of the U.S. dollar relative to other currencies can change the trade balance within economies and, in turn, affect the economic activity and liquidity in the economy as businesses finances and their access to sources of funds can vary. Furthermore, the exchange rate also affects the availability of credit in the economy. A high exchange rate can increase the attractiveness of foreign investment, leading to an inflow of capital into the U.S. economy. This can lead to increased credit availability and lower borrowing costs, thereby increasing liquidity in the economy. On the other hand, a low exchange rate can discourage foreign investment, resulting in lower credit availability and higher borrowing costs, which can reduce liquidity in the economy (Huang and Stoll, 2001; Bianchi et al., 2021). Hence, policymakers are mindful of the impact of the exchange rate on liquidity and implement effective measures to stabilize the currency, maintain economic stability, and promote sustainable growth. Central banks can intervene in currency markets to prevent excessive fluctuations in the exchange rate.

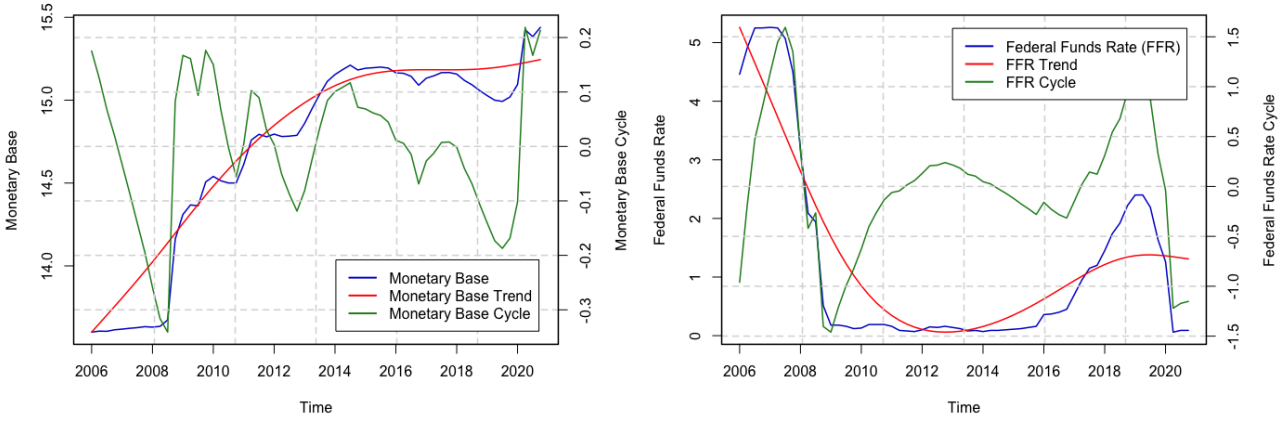
Finally, we also include the *Consumer Price Index (CPI)*, a measure of inflation, which can track changes in the prices of goods and services over time. It has a significant impact on the business cycle, as it affects consumer purchasing power, business profits, and investment decisions (McCallum, 2001; Galí, 2015; Hommes and Lustenhouwer, 2019).

Overall, federal funds rates, money supply, CPI, and exchange rates and their interaction play important roles in determining liquidity and economic activity. policymakers attempt to promote economic activity through their tools such as fiscal policies and monetary policies. The government can implement fiscal policies like tax cuts and government spending to stabilize the economy. Central banks can also exploit monetary policy tools such as interest rate adjustments, open market operations, and reserve requirements to influence liquidity and the business cycle.

FIGURE 4.6: Exogenous Variables time series

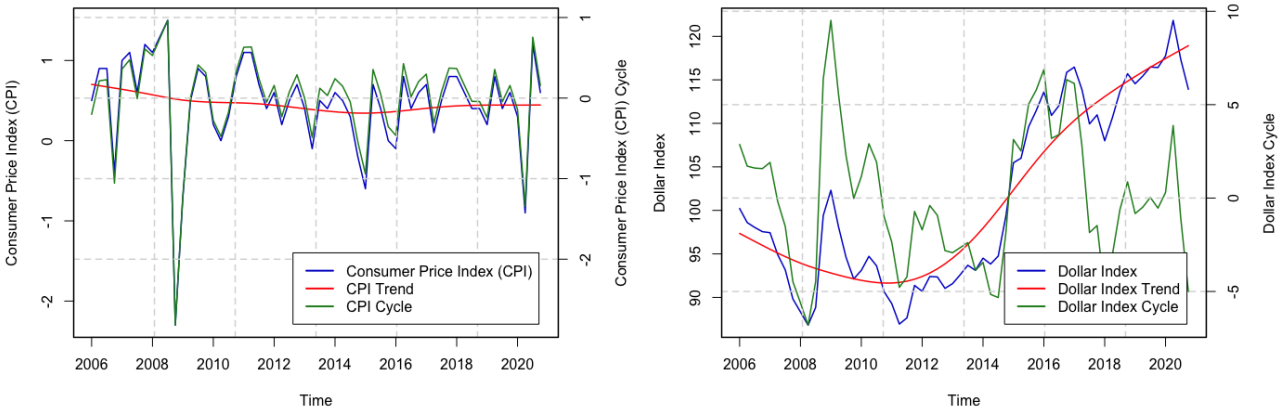
(A) Monetary Base

(B) Federal Funds Rate



(C) Consumer Price Index

(D) Dollar Index



Note: Figure depicts the time series of exogenous variables used in the model. The exogenous variables are the Monetary Base, Federal Funds Rate, Consumer Price Index, and Dollar Exchange index. Each panel plots the original variable, the trend, and cyclical components of the variables that are calculated by the Hodrick–Prescott (HP) filter and explained in Appendix B.6. The right vertical axis of each panel is the scale of each exogenous variable, and the left vertical axis represents the scale of the cyclical component. The horizontal axis shows the yearly time period.

Data source: Plotted by the author using the Datastream and the FRED datasets.

4.3.2 Structural Vector AutoRegressive (VAR) model

This section focuses on the description of the structural VAR model, which is a practical tool to show the dynamic effects of variables of interest over time. We first explain the model setup in part 4.3.2.1. We show how SVAR representation represents the processes of the model that are dependent over time, and how to analyze the dynamic interactions of our variables by tracking the effect of an impulse on our variables within the system. The identification

issues associated with the "structural" VAR and how we deal with the problem are explained in Subsection 4.3.2.2. The model specification is illustrated in part 4.3.2.3. Further, we elaborate on two theoretical implications of the model including the Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs) respectively in segments 4.3.2.4 and 4.3.2.5.

4.3.2.1 Model Setup

The Structural Vector Auto-Regressive (SVAR) models are an outstanding tool in macroeconomics to investigate the impacts of shocks on a system of variables. In these models, the unobserved structural innovations serve the information that is unrevealed or undisclosed in the reduced-form VAR model. We intend to determine the system's responses to this type of isolated shock, which can be visualized by the impulse-response functions approach.

It is initially assumed we have the K dimentional multivariate VAR representation of order p, where the process of y_t is a sequence $\{y_t\}_{t=0}^{\infty}$ defined by the following linear p-order equation,

$$y_t = \mu + A_1 y_{t-1} + ... + A_p y_{t-p} + e_t \tag{4.6}$$

where $y_t = (y_{1t}, ..., y_{Kt})'$ indicates a $(K \times 1)$ vector of time series variables (endogenous variables), coefficient A_i $(i = 1, ..., p)$ are $(K \times K)$ matrix, and μ denotes the intercept coefficient and is mapping the variable of interest to its previous value $(t - p)$, which can be interpreted as the time-invariant deterministic terms.

4.3.2.2 The Identification Problem

The VAR model is a very useful method to explain impulse response functions and investigate the connection between the variables of interest. The model, however, has shortcomings in

its interpretation. The impulse responses are not unique and in general, the set of impulse responses that can impact the system is ambiguous and varying, so the non-sample information is required to choose the appropriate set from the underlying model (Lütkepohl, 2005). VAR representations are considered as reduced form models in econometric terminology, and it is essential to impose some structural restrictions in order to identify the shocks and accordingly investigate impulse response function and forecast error variance decomposition.

More specifically, the innovation e_t in Equation 4.6 may be correlated contemporaneously i.e. σ_e may not be a diagonal matrix. This implies that Φ_i matrices in Equation 4.12 will not represent the relationships between the endogenous variables correctly, hence there will be no isolated shocks in the system of equations which can make the interpretation of innovations in matrix e_t impossible. To overcome this issue, we need to identify the model's parameters and impose restrictions on the model in order to find economic insight and structural interpretation of the response of the variables. The choice of identification is one of the main challenges of this study since the approaches are quite arbitrary and thus unsatisfactory unless they build upon a theoretical model or there are specific justifications behind the approach. In Section 4.2.2 we reviewed the possible approaches to identify the impulses and the underlying SVAR model.

Our strategy to specify unique innovations and impulse responses is first to estimate a simple baseline model with the least restrictive identification method and then use other studies to build an alternative identification model and implement a robustness check to make solid arguments about the model under scrutiny. The departure point to build the identification scenarios is based on the following structural form model,

$$\mathsf{A}y_t = \mu + A_1 y_{t-1} + ... + A_p y_{t-p} + \mathsf{B}\epsilon_t \tag{4.7}$$

$$y_t = \mu + A_1^* y_{t-1} + ... + A_p^* y_{t-p} + \mathsf{A}^{-1}\mathsf{B}\epsilon_t \ , \qquad t = 1, ..., T \tag{4.8}$$

where $A_i^* = \mathsf{A}^{-1}A_i$ $(i = 1, ..., p)$. The vector e_t contains reduced-form residuals or innovations at time t, which are assumed serially uncorrelated and follows $e_t \sim (0, \sigma_e^2)$ i.e., e_t is a white

noise with mean $E(e_t) = 0$, time-invariant variance σ_e^2, and $cov(e_t) = \Sigma_e = \mathsf{A}^{-1}\mathsf{B}\Sigma_\epsilon\mathsf{B}'\mathsf{A}^{-1'}$. Also, the nonsingular $(K \times K)$ matrix B captures the contemporaneous effects of the structural shocks upon the variables of the system.

For analyzing the impulse response we are mainly interested in interpreting the unexpected part of the simultaneous equations system or shocks rather than specifying the relationship between the endogenous variables. We thus attempt to identify the structural shocks ϵ_t from the reduced form residuals or forecast errors e_t in Equation 4.6. This implies the following relation,

$$e_t = \mathsf{A}^{-1}\mathsf{B}\epsilon_t \tag{4.9}$$

meaning that the reduced form error e_t can be considered as linear functions of the structural shocks ϵ_t with which the relationships between the reduced form residuals are characterized using the covariance matrix $cov(e_t) = \Sigma_e = \mathsf{A}^{-1}\mathsf{B}\Sigma_\epsilon\mathsf{B}'\mathsf{A}^{-1'}$ in Equation 4.7, where Σ_ϵ is the covariance matrix of the structural shock ϵ_t. The structural shocks of the model are considered uncorrelated Σ_ϵ, and thereby it is a diagonal matrix. If the errors are correlated, it is hard to measure directly the impact of any change in an error since the shock cannot be kept constant when a shock occurs. This is required for a meaningful impulse-response analysis (Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

Yet, with no further model specification, the equation of Σ_e holds for every matrix A and B which decomposes the variance-covariance matrix Σ_e. Thus, additional restrictions are required to construct a unique matrix A and B. The identification of matrix B enables us to find economic insight and structural interpretation on the response of the variable of interest. After estimating the VAR model in Equation 4.6, the estimated reduced-form residual $\hat{e}_t$ and the corresponding estimated $\hat{\Sigma}_e$ is the first step for the subsequent identification methods.

Once we specify the number of lag length p for the VAR(p) model, the restrictions are imposed to estimate the structural parameters. The SVAR parameters are not identified without the restrictions, i.e. it is not possible to solve uniquely the structural parameters A, B, A and Σ_e given values of the reduced form parameters Σ_ϵ and A^*. From the Relation 4.9 we have $\frac{K(K+1)}{2} = 10$ equations while there are $K^2 = 16$ elements for each matrices A and B. This implies that with $K = 4$ the overall number of $2K^2 - \frac{K(K+1)}{2} = 22$ restrictions on the matrices A and B are required to obtain the exact identification. we have imposed the just-identified restriction in order to avoid over-simplifying and placing too many restrictions on the system.

The *baseline model scenario* for the identification is to leave out the matrix A by setting the $\mathsf{A} = I_K$ and only identify the diagonal matrix B where the diagonal elements reflecting the standard deviation of the error terms of the system of equations. The uncorrelated diagonal matrix provides a straightforward and transparent choice to identify the structural shocks and an easy simple way to interpret the impulse response results and explain the underlying dynamics of the system. This also allows the model to avoid any biasedness rooted in the wrong determination of the immediate impact of endogenous variables in matrix A.

The *second scenario* of the identification follows the standard approach where the relations between shocks arise due to instantaneous correlations between endogenous variables. This implies that we look at the system such that each variable depends on the contemporaneous effects of other variables instead of having a variable that only depends upon past values of other variables. The matrix B can be still considered as an uncorrelated diagonal matrix as we had in the first scenario. Given that the structural shocks are uncorrelated and there are 12 zero restrictions on B matrix, there are 10 additional restrictions are required to identify the full model. The diagonal is normalized to 1 and the off-diagonal is restricted based on the related literature of the study. We use just-identifying restrictions as represented in the form of the following structural matrix A and B. As discussed earlier in 4.3.2.2, it is impossible to estimate all the coefficients in matrix A without some restrictions. Our approach to identifying

the parameters of matrix A is to make the system recursive, as it is proposed by Wold (1951).[16]

We attempt to extract the choice of restriction by the studies done on the relationships between the variables of interest. The restrictions imposed on matrix A are similar to Cholesky restrictions and are consistent with the studies done so far. Some research has been conducted about the relationship between the financial network centrality and liquidity ratios. The relationship between account receivables/payables and other short-term elements of the balance sheet is complex and interconnected. Changes in one element can affect the levels of others, which can potentially affect the firm's ability to meet its short-term obligations. However, the elements A_{12} and A_{21} are primarily identified by the studies of Allen and Gale (2000) and Acharya and Yorulmazer (2008) which show highly connected institutions may be more susceptible to contagion and liquidity risk, which can lead to a sudden withdrawal of funding and a loss of liquidity. We also use Altinoglu (2021) argument about the role of network effects on the output in order to identify A_{13}, A_{23}, A_{31}, and A_{32}. $\mathsf{A}_{14} = 0$ and $\mathsf{A}_{24} = 0$ are assumed as no contemporaneous impact since the repo rates are determined endogenously but not vice versa (Téllez-León et al., 2021). The elements A_{34} and A_{43} are also inspired by Taylor (1993).[17] This argument and the corresponding reduced form residuals Equation 4.9 can be specified as the following matrix form;

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{pmatrix} \begin{pmatrix} e^N \\ e^{LR} \\ e^{GDP} \\ e^R \end{pmatrix} = \begin{pmatrix} b_{11} & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 \\ 0 & 0 & b_{33} & 0 \\ 0 & 0 & 0 & b_{44} \end{pmatrix} \begin{pmatrix} \epsilon^N \\ \epsilon^{LR} \\ \epsilon^{GDP} \\ \epsilon^R \end{pmatrix} \tag{4.10}$$

[16] The combination of triangularity and uncorrelated shocks is a numerical method for estimating a recursive system, which is known as the Cholesky decomposition. In this method, the ordering choice of variables is identified by theoretical or institutional ideas (Wold, 1951; Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

[17] The identification of A and B are mainly determined by the theoretical background as there is no unique structure. The second scenario is built under some assumptions based on the related literature. For some cases, a different way of restrictions was imposed, and found negligible differences in results. Nevertheless, there is some degree of uncertainty in the second identification approach, and the structure of matrix A is only applied to check the robustness of the base scenario.

4.3.2.3 Model Specification

This segment characterizes the estimation strategy by specifying the model and identifying shocks and impulses in order to produce reasonable results. Our corresponding SVAR representation of Equation 4.7 then can be formulated as:

$$\mathsf{A}\,\mathcal{C}(Y_t) = \alpha + \sum_{i=1}^{p} A_p\,\mathcal{C}(Y_{t-i}) + \delta\,\mathcal{C}(X_t) + \mathsf{B}\,\epsilon_t \tag{4.11}$$

where $Y_t = (N_t, LR_t, GDP_t, i_t)'$ for the period $2006Q1$ to $2020Q4$, where Y_t is the vector of the U.S. macro-financial time series variables, the real GDP (GDP_t), an overnight repo rate (i_t), liquidity ratio (LR_t), and the network indices (N_t) are the variables of interest that are explained in Section 4.3.1. Since further generalizations of the model are desirable in practice and help to have better results, we also include further stochastic variables in addition to the deterministic part. X_t is a vector of unmodeled exogenous variables representing the money supply provided by the U.S. central bank, federal funds rate, dollar exchange rate, and inflation rate, respectively, for our sample period. These are the variables that are expected to affect the macroeconomic outcomes.[18] $\mathcal{C}(\cdot)$ denotes the time series cycle calculated by the HP filter explained in Appendix B.2. Note that, as the process y_t shows unit root process (further explanation can be seen in Section 4.4), we use the cycle component of the time series $\mathcal{C}(\cdot)$ and is compatible with a stationary generation process. Moreover, the number of lags can be determined by the selection criteria that are explained further.

Note that as part of the data processing and cleansing technique, all the variables are normalized by min-max normalization, i.e. $Y_t = \frac{Y - Y_{min}}{Y_{max} - Y_{min}}$. The main reason is to make the variables homogeneous over all records and fields in order to improve the data quality.[19]

[18] In this study we do not intend to calculate the dynamic multipliers of the exogenous variables or investigate the impulse responses to innovation for the exogenous variables. The exogeneity is only specified by incorporating the exogenous variables in the structural equation.

[19] The min-max normalization is chosen over the z standardization $Y_t = \frac{Y - mean(Y)}{std(Y)}$ to avoid any presumptions about the distribution of the data (see Ali et al. (2014) and Asesh (2021) to find some helpful application of data preprocessing normalization techniques).

4.3.2.4 Impulse-Response Functions (IRFs)

Impulse response functions investigate the effect of isolated shocks on the variables of the model with respect to a particular response lag (delay). The response matrices of Equation 4.6 can be characterized with recursive substitution given starting at some infinite time i,

$$\mathsf{A}A(L)y_t = \mu + \mathsf{B}\epsilon_t \tag{4.12}$$

$$y_t = \mathsf{A}^{-1}A(L)^{-1}\mu + A(L)^{-1}\mathsf{A}^{-1}\mathsf{B}\epsilon_t \tag{4.13}$$

$$= \nu + \Phi(L)\mathsf{A}^{-1}\mathsf{B}\epsilon_t = \nu + \sum_{i=0}^{\infty}\Phi_i\mathsf{A}^{-1}\mathsf{B}\epsilon_{t-i} = \nu + \sum_{i=0}^{\infty}\Theta_i\epsilon_{t-i} \tag{4.14}$$

where the reduced form lag polynomial is defined as $A(L) = I - A_1L - A_2L^2 - ... - A_pL^p$, and ν denotes the unconditional mean of observable variables. The $\Theta_i(= \Phi_i\mathsf{A}^{-1}\mathsf{B})$ summarizes the information of dynamic parameters in Φ_i $(i = 1, 2, 3, ...)$ and of the structural matrix $\mathsf{A}^{-1}\mathsf{B}$. Matrix Θ_0 then represnts matrix $\mathsf{A}^{-1}\mathsf{B}$. Thus, the elements of Θ_i can be interpreted as the responses of the system to structural shocks ϵ_t. Here we wish to investigate the effect of a unit change in a structural shock on the relevant variables. Then, the effects of a change in the initial shock on y_t has the following dynamic,

$$\frac{\partial y_t}{\partial \epsilon_{t-i}} = \Theta_i \tag{4.15}$$

This shows that the dynamic multiplier Θ_i depends solely on the time lag i, which represents the number of periods that separate the occurrence of the disturbance ϵ_{t-i} from the observation of the output variable y_t. However, the multiplier is independent of the specific observation time t. This implies that the value of Θ_i remains constant regardless of which time period t is the output observation y_t, and the dynamic relationship between the disturbance and the output remains stable over time.

4.3.2.5 Forecast Error Variance Decompositions (FEVD)

Forecast Error Variance Decomposition (FEVD) explains the relative contribution of each structural shock to the variation of the variables of interest. The technique helps in analysing the relative importance of different shocks in explaining the fluctuations of the variables over a forecast horizon h. The FEVD formula for a given variable y_{kt} with respect to the shock ϵ_{it} at a specific forecast horizon h is typically written in the form:

$$FEVD_{ki}(h) = \frac{\sum_{j=0}^{h-1} \Theta_{ki,j}^2}{\sigma_k^2(h)} \tag{4.16}$$

where $\Theta_{ki,j}$ represents the element in the k-th row and i-th column of the matrix Θ_j at lag j, so the numerator implies quantifies the contribution of a specific structural shock to the forecast error variance of a variable y_{kt} at a specific forecast horizon h. The denominator $\sigma_k^2(h)$ is the h-step ahead forecast error variance of the k-th variable and can be computed by $\sigma_k^2(h) = \sum_{j=0}^{h-1} \sum_{i=1}^{K} \Theta_{k_i,j}^2$, which is the sum of squared contributions from all structural shocks across lags up to $h-1$. Additionally, the h-step ahead forecast error for the multivariate time series y_t is a linear combination of the structural shocks ϵ_{t+1} to ϵ_{t+h}, and can be presented mathematically as $y_{t+h} - y_{t|t}(h) = \Theta_0\epsilon_{t+h} + ... + \Theta_h\epsilon_{t+1} = \sum_{j=0}^{h-1} \Theta_j\epsilon_{t+h-j}$ (more detailes can be found in Lütkepohl (2005)).

4.4 Empirical Results

This section reports the steps for estimating the SVAR model. This starts with explaining the model specification including the lag selection, stationary, and stability tests in Segment 4.4.1. Additionally, analysis of impulse response functions and forecast error variance decomposition have been explained afterward in 4.4.2 and 4.4.3, respectively.

4.4.1 Model Specification

The first step of implementing SVAR model is to decide on the orders of $AR(p)$ model and specify the lag length p by applying different information criteria; Different model selection criteria such as Akaike Information Criterion (AIC), Hannan-Quinn (HQ), Schwarz (SC), and Akaike's Final Prediction Error (FPE) criterion are carried out to select the length of p. Table 4.1 reports the selection criteria and their corresponding scores suggested by each criterion for the AR orders of 1 to 5 (see Table B.3a and B.3b in Appendix B to see the scores for each selection criteria). They propose orders of 1 or 4 based on different selection criteria since these orders minimize each criterion. We apply AIC and FPE criteria over the HQ and SC as they result in less parsimonious specifications with more parameters. Thus, the results were obtained using criteria AIC and FPE where $p = 4$ is suggested, and it is also more compatible with the quarterly sample size of $T = 60$.

TABLE 4.1: The best AR lag length order suggested by each criterion

Selection criterion	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
AR order	4	1	1	4

Note: Table reports the selection criteria and their corresponding scores for the AR orders of 1 to 5.

The second step is to analyze the stationarity of the data generating process. This is a necessary assumption in time series SVAR analysis to keep the statistical properties of the time series (e.g., mean and variance) constant over time (Lütkepohl, 2005; Kilian and Lütkepohl, 2017). We apply Augmented Dickey–Fuller (henceforth: ADF) test to check the null hypothesis of having a unit root against the alternative of having the stationarity of the data. Table B.4 in the Appendix shows the original variables compared to the cycle of variables in y_t for AR order selected by the model selection criteria. Since all original variables contain the time-varying patterns and non-stationary trend, we perform the Hodrick and Prescott (1997) method explained in Appendix B.6 and use the cycle component as the transformation method to study

the business cycles and fluctuations in the system. The results suggest that the HP cycle trend for the GDP, repo rate, quick ratio, and network indices reject the null hypothesis of unit root at a 5% significant level, and thereby, the cyclical part of the variables are stationary.

After the specification of the lag length p and unit root test, we estimate the SVAR model using the U.S. macro-financial time series explained in Section 4.3.1. The multivariate VAR then contains the real GDP (GDP_t), a repo interest rate (i_t), quick ratio (QR_t), and the network index (NI_t). Hence, the vector of time series variables for the sample period $2006Q1$ to $2020Q4$ is $y_t = (PR_t, QR_t, GDP_t, i_t)'$. Finally, using the reduced form VAR(4), we estimate the structural parameters by imposing the just-identifying restriction identified in Section 4.3.2. The results of estimating the structural coefficients (parameters) are reported by following matrix A and B,

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \underset{(0.46)}{0.94} & 1 & 0 & 0 \\ \underset{(0.0009)}{-0.06} & \underset{(0.039)}{0.013} & 1 & 0 \\ \underset{(0.001)}{-0.28} & \underset{(0.004)}{-0.24} & \underset{(0.19)}{-0.012} & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.119} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.17} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.07} \end{pmatrix} \tag{4.17}$$

where each element shows the parameter estimate and the figures in parentheses are the corresponding p-values.[20] The matrix A in 4.17 represents the contemporaneous relationship between the endogenous variables under study. According to the reported matrix A, the coefficient 0.94 (associated with the relationship between QR_t and NI_t) has a p-value of 0.46. This p-value is higher than conventional significance levels (such as 0.05), suggesting that the relationship might not be statistically significant. However, the relationship between GDP_t and NI_t as well as the effect of GDP_t and QR_t with the coefficient of -0.06 and 0.013 are statistically significant. The coefficients for the variable i_t also have p-values of 0.001 and 0.004, suggesting statistical significance for the relationships between the interest rate i_t, NI_t,

[20] The robustness results for different scenarios can be found in B.4.4.1.

and QR_t, respectively, while the relationship between i_t and GDP_t may not be statistically significant at the conventional level with a p-value of 0.19.

The matrix B reports the estimated standard deviations of the shocks or errors for NI_t, QR_t, GDP_t, and i_t, respectively. Therefore, the diagonal elements of B not only represent the estimated standard deviations of the errors but also directly determine the magnitude of the shocks' impact on each variable in the system. Higher standard deviations indicate greater unpredictability or variability in the shocks and, subsequently, a larger potential influence of these shocks on the variable in question. According to matrix B, the highest volatility respectively associated with the network effect, quick ratio, GDP, and interest rates with the elements of 0.119, 0.17, 0.09, 0.07 on the diagonal. After all, note that what we are mainly interested in is interpreting the unexpected part of the simultaneous equations system or shocks in matrix B rather than specifying the relationship between the endogenous variables in matrix A although estimated parameters of matrix A contribute to the accuracy of the results. Once we identify and estimate the structural model and its corresponding parameters, the effects of the shocks ϵ_t can be analyzed by the impulse response function in the next Section 4.4.2.

4.4.2 Impulse Response Functions (IRFs) Analysis

Impulse Response Functions (IRFs) attempt to investigate the effects of shocks (i.e., impulses) in the system of equations. IRFs trace out a change (here, two standard deviation shocks) to endogenous variables of the system and their effects on all the endogenous variables while holding other factors and shocks fixed.[21] This part concentrates on shocks by first, identifying

[21] The decision to employ a two-standard-deviation shock rather than a moderate one-standard-deviation shock was grounded in multiple considerations. Given the research's focus on variables with short-term dynamics, where one-standard-deviation changes are common, opting for a stronger shock became desirable. The magnitude of shocks aimed to delve into the system's response to significant disruptions that might not be adequately captured by a single standard deviation shock. Considering potential severe economic scenarios, employing larger shocks facilitates a more comprehensive grasp of the system's dynamics and resilience. Furthermore, the use of a larger shock allows for the evaluation of the system's stability and robustness in extreme conditions. This choice aligns with the objective of stress testing and assessing the system's reaction to extraordinary events, enabling a more realistic appraisal of potential outcomes in high-stress scenarios.

the relevant shocks and then by describing the response of the system to them using analyzing the propagation mechanism of shocks through the impulse responses and investigating the forecast error variance decomposition.

Two standard deviation shocks are introduced to the endogenous variables through the error terms in Equation 4.6. These shocks simultaneously affect all the variables of interest. The immediate effects of the shocks are evident not only in the same time period but also in subsequent periods, as our $VAR(4)$ system incorporates lagged variables up to four periods. This means that the current and past four periods' values jointly contribute to explaining the variables' behavior. $VAR(4)$ model also employed Bootstrap resampling to tackle the uncertainty in estimating Impulse Response Functions (IRFs). This technique generates a distribution of potential IRF outcomes by creating numerous resamples (here, 1000 times) from the original dataset. These samples capture variations in the data and help assess the robustness of the IRF estimates.

Figure 4.7 visualizes the impression of the dynamic interaction through the system and shows graphically the response of variable i to a two standard deviation shock (forecast error) in variable k. More specifically, we shed light on the patterns of fluctuations including the magnitudes and lengths of responses to the key endogenous variables. Figure 4.7 shows the effects of *two standard deviations* shocks to the variables from the channel of network effect, quick ratio, interest rate, and the GDP of the US economy. All the variables shown in Figure 4.7 contain only temporary (transitory) shocks rather than permanent shocks. However, some of the transitory shocks are quite persistent and take a long time to make any changes. The graph represents that all the variables' responses occur at the same time because of the contemporaneous effect in matrix A.

Figure 4.7 represents that the largest responses in the whole system are for the past values of the endogenous variables itself. With a two-standard deviation impulse, the largest responses are captured by the liquidity ratio (i.e., quick ratio) and the network effect with 0.2 and 0.15,

respectively. The GDP and the interest rate (i.e., repo rate) come after, both with 0.1 percent. However, the GDP by far is the most volatile variable among all the endogenous variables within the 20 periods. The GDP shock also is the last variable in which the fluctuation dies away.

Within all the interest rate impulses, the largest innovation is from the past values of the interest rate itself. The impulse to repo rate (i.e., interest rate) increases the repo rate significantly up to about 0.1 percent. However, the impulse tapers off immediately within 5 quarters. The liquidity ratio, network effect, and the GDP respectively have the biggest fluctuations in the range of -0.05 and 0.05, and they all converge to zero almost after 10 periods. The GDP response and impulse from and to the interest rate have the smallest fluctuations in the whole system.

The second column of Figure 4.7 shows the response of our endogenous variables to the 2 standard deviation output shock. In terms of the output impulse, the biggest fluctuation is for the past values of the output itself with the range of -0.05 and 0.05, and it dies out after fluctuating around the baseline after 20 periods. The second volatile response is for the liquidity ratio within the range of -0.04 and 0.04 and fluctuated for about 15 quarters and then faded away. Although the variance degree of the network is the strongest between the liquidity ratios with the jump to more 0.05 and dies longer, the other indices of the network effects show less suffered by the output shock. The least volatile response is when the output impulse generates negligible fluctuation in the interest rate.

The third column of Figure 4.7 shows the response of our endogenous variables to the 2 standard deviation liquidity ratio (i.e., quick ratio) shock. Although the biggest effect is for the past values of the liquidity ratio itself, the impulse tapers off very quickly after 5 quarters. The network effects capture the second largest effects, but it takes longer for the fluctuations to converge to zero, almost 10 periods. Compared to the other variables, the GDP response has experienced more fluctuations than the other variables and it lasts about 20 periods to fade

away. The first panel in the quick ratio impulses shows negligible volatile indicators within all the variables of interest.

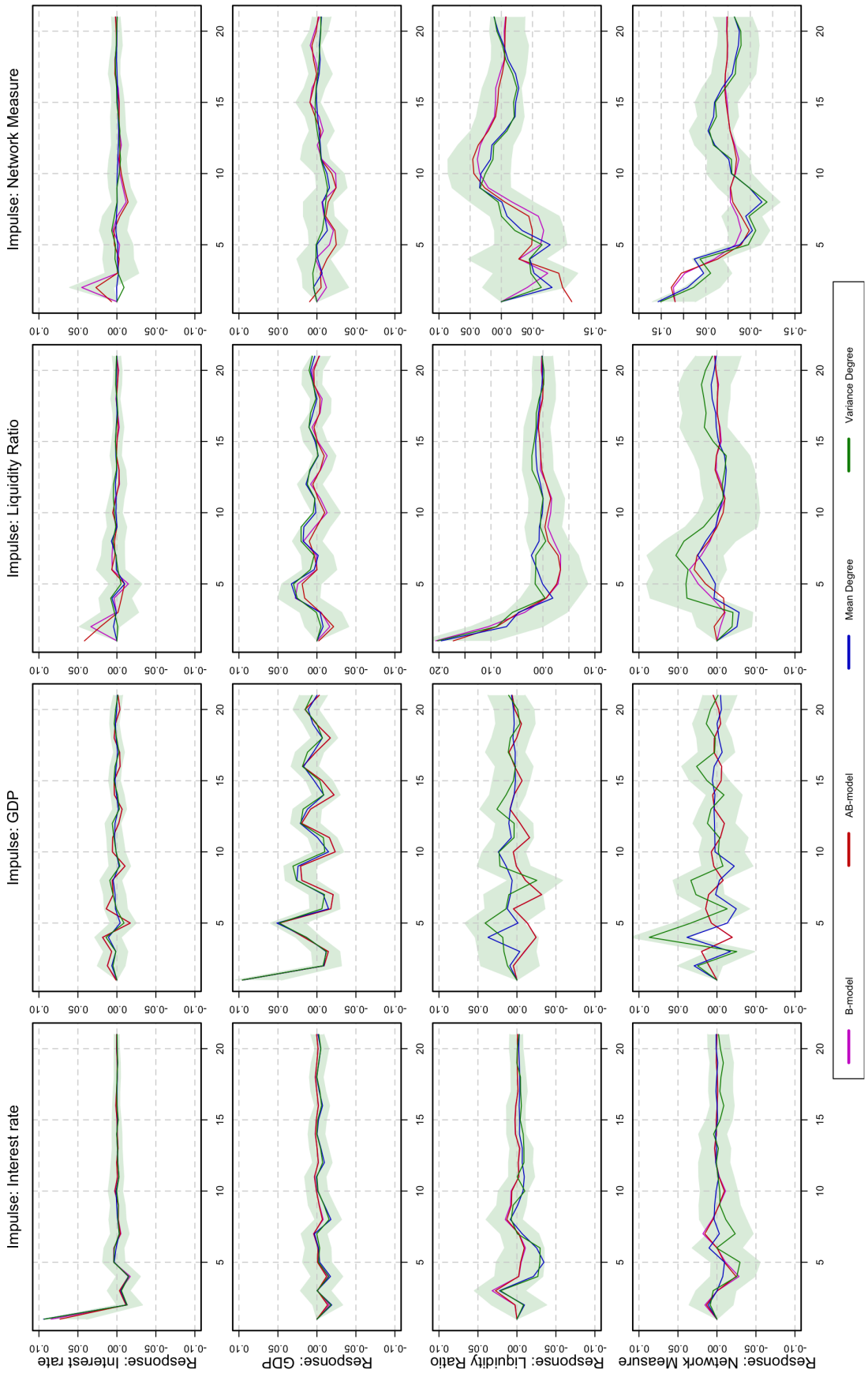
Regarding the network effect, after the past values of network indicators, the most fluctuations happen for the liquidity ratio (i.e., quick ratio) response with the range of -0.08 and 0.05. This can be explained by the firm's approaches to switching between the methods of financing. The GDP response comes next with mild changes in the range of -0.025 and 0.01 compared to the interest rate (i.e., repo rate) response with negligible fluctuations. The output changes fade away longer than the repo rate where the fluctuation dies out quickly after the 3 periods. The biggest innovation in the financial data is concerned with liquidity ratio and network effects when the structural liquidity ratio shocks and network effects shock are seen to induce the variable itself for the first period and then it tapers off to zero after 5 quarters.

Additionally, the Bootstrap resampling method is also employed to account for uncertainty in the estimation of IRFs in the above SVAR model. The resampling method generates a distribution of potential IRF outcomes by generating 1000 resamples from the original dataset. For each of these resampled datasets, the SVAR model is re-estimated, and corresponding Impulse Response Functions are computed and depicted collectively in Figure 4.7. To quantify the uncertainty surrounding the estimated IRFs, a 95% Confidence Interval (CI) is constructed, which signifies that there is a 95% probability that the actual IRFs lie within the calculated error bands (see the light green band around the line charts). By generating these resampled IRFs, the bootstrap procedure reveals the extent of variability and potential errors that can arise in our IRF estimates. The error bands serve as visual representations of the range within which the true IRFs are likely to be situated.

4.4.3 Analysis of Forecast Error Variance Decomposition (FEVD)

We also estimate Forecast Error Variance Decompositions (FEVD) along with the impulse response functions. FEVD is a part of structural analysis that reports the proportion of variations in the endogenous variables of interest which are explained by an impulse (or a shock). FEVD "decomposes" the variance of the forecast error into the contributions of each variable from specific (exogenous) shocks. More Intuitively, this exhibits the importance of each shock or change over time and how much a shock can explain the variations of each variable in the model. FEVDs of the system under study are reported in Table 4.2, the results of which are estimated in VAR representation 4.6 for investigating the driving forces of cyclical fluctuation. Variance decomposition provides a general insight into the "impact" rate of innovations in our network economy. The FEVD in fact evaluates the importance of different impulses by specifying the relative proportion of variance that each innovation contributes to the total variance of each variable.

FIGURE 4.7: SVAR Impulse Response Functions (IRFs)



Note: The Figure exhibits the Impulse Response Functions (IRFs) for four identification scenarios and the endogenous variables of interest including repo rate, real GDP, quick ratio, network index, mean degree distribution, and variance degree distribution. Each panel contains four line charts each reflecting the corresponding identification scenario. The vertical axis of each plot shows the magnitudes of the impulses, and the horizontal axis represents the persistence of each shock. 95% Confidence Interval (CI) is constructed to address the uncertainty of IRFs.

Data source: Calculated and plotted by the author.

Similar to impulse response functions in 4.4.2, FEVDs are generally presented graphically in a bar graph to visualize the proportion of variances. Figure 4.8 illustrates the variance decomposition for each variable, including 'network index,' 'repo rate,' 'liquidity ratio,' and 'GDP,' with respect to our designated variable of interest. This visualization serves to provide a graphical representation of the information presented in Table 4.2. The figure shows the composition of the error variance across innovations to all the variables of interest at each time period. For the network/ liquidity ratio/GDP/interest rate system, about 68% of the 1-st step forecast error variance of repo rate (i.e., interest rate) is accounted for by own innovations and about 19% is accounted for by network effects. For long-term horizon 20 period forecasts, 59 percent and 18% of the forecast error variance are accounted for interest rate and network effects, respectively. For any forecast horizon, the quick ratio and GDP innovations combined contribute less than 20% to the forecast error variance of interest rate. In the entire horizon, the quick ratio varies from about 10 to 12%. However, the output shock started in the 2-nd step forecast error with only 1% and increased to around 10% for the long-term horizon 20.

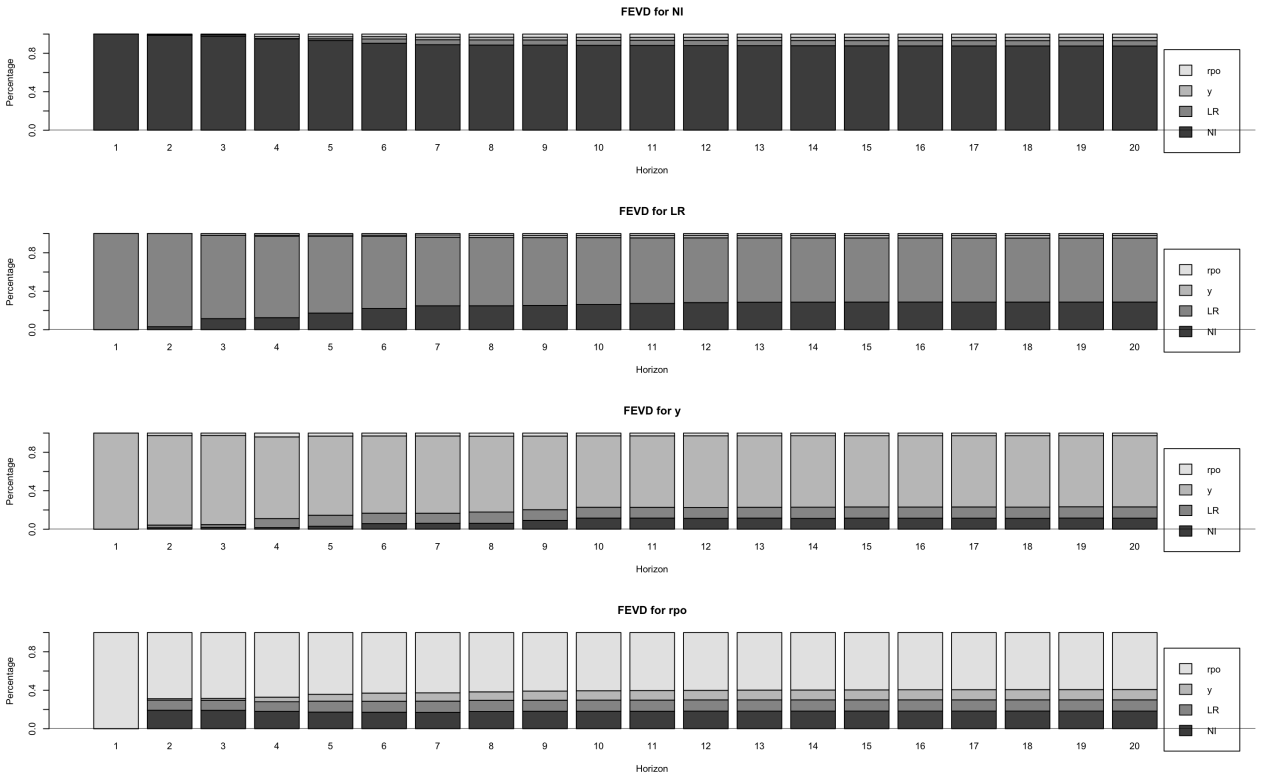
Regarding the GDP, we observe that more than 90% of the variations in GDP can be explained by the output shock in the first 3 time period. As we move further on to the next periods in the long term, the share of variation in GDP explained by output innovation goes on decreasing to approximately 75% by time period 20. On the contrary, approximately 1% of the 2-st step error variance of the output is accounted for by centralities' impulses, and this proportion goes further and stabilizes after the 10 time period at about 11%. Similarly, the quick ratio's contribution is about 0.02 and grows to 11% in the longer horizon. The repo rate shock has a negligible share among the other impulses. The interest rate shocks rank 4rd among all the shocks. we observe only small fractions of the error variances of GDP are explained by the interest rate impulses with less than 3%.

We similarly construct FEVD for quick ratio in response to all the variables' innovations under study. The main proportion of variations in the quick ratio is explained by its own effect by capturing the whole impact at the first step. As innovation moves further, it drops

significantly to about 66% by time period 20. The remaining proportion of forecast error variance in liquidity ratio can be reported by the other variables - repo rate, GDP, and network effect - with less than 13% combined by 4th periods in the short-term to around 30% in period 20. Concerning the forecast error in network effect, the centralities' shock contributes the most to the volatilities of receivables/payables with more than 95%. As the horizon expands, the network impact reduces to about 87%, and this thereby substitutes with other variables innovations, mainly quick ratio. Quick ratio ranks second in explaining variations of the network with a maximum of 5 percent. The smallest fractions of the error variances of network centralities are related to the repo rate and GDP, where their shock stands third and fourth in explaining the changes in network centralities with the range of 0.003 to 3%.

Overall, the results highlight the role of network effects and the quick ratio among the liquidity-related variables. Among the self-innovation variables, the highest variations are accounted for by the network effect, quick ratio, GDP, and repo rate, with averages of approximately 93%, 83%, 81%, and 64%, respectively. For non-self-innovations, the highest proportion of variation is observed in network data and quick ratios. Regarding the second-highest rank in system fluctuations, there is no consensus among the robustness checks of the results. The baseline scenario shows a high proportion of fluctuations in the interest rate (i.e., repo rate) derived from the network data. However, other results demonstrate a high variation in the quick ratio concerning GDP fluctuations.

FIGURE 4.8: Forecast Error Variance Decomposition (FEVD) of the variable of interests



Note: The Figure exhibits the Forecast Error Variance Decomposition (FEVD) for the B-model scenario using the endogenous variables of interest including repo rate, real GDP, quick ratio, and network index. Each panel contains bar charts showing the proportion of variations for a variable. The vertical axis denotes the proportion of each shock, and the horizontal axis represents the forecast horizon h.

Data source: Calculated and plotted by the author using FRED.

TABLE 4.2: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/network effect system

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Network effect	Quick ratio	GDP	Repo rate
Repo rate	1	0.00	0.00	0.00	1.00
	2	0.19	0.10	0.01	0.68
	3	0.19	0.10	0.01	0.68
	4	0.18	0.10	0.04	0.67
	5	0.17	0.11	0.07	0.64
	10	0.18	0.11	0.09	0.60
	20	0.18	0.118	0.10	0.59
GDP	1	0.00	0.00	1.00	0.00
	2	0.01	0.02	0.93	0.02
	3	0.01	0.02	0.92	0.02
	4	0.01	0.09	0.84	0.03
	5	0.03	0.11	0.82	0.03
	10	0.11	0.11	0.74	0.02
	20	0.11	0.11	0.74	0.02
Quick ratio	1	0.00	1.00	0.00	0.00
	2	0.03	0.96	0.0003	0.00
	3	0.11	0.86	0.001	0.01
	4	0.12	0.84	0.01	0.01
	5	0.17	0.79	0.01	0.01
	10	0.26	0.69	0.02	0.01
	20	0.28	0.66	0.02	0.01
Network effect	1	1.00	0.00	0.00	0.00
	2	0.98	0.00	0.003	0.007
	3	0.97	0.003	0.012	0.005
	4	0.95	0.003	0.02	0.02
	5	0.93	0.01	0.02	0.02
	10	0.88	0.05	0.02	0.03
	20	0.87	0.05	0.03	0.03

Note: The Table reports the Forecast Error Variance Decomposition (FEVD) for the B-model scenario using the endogenous variables of interest including repo rate, real GDP, quick ratio, network index for the forecast horizon period $h = 20$.

Data source: Calculated and plotted by the author using FRED.

4.5 Concluding Remarks

This study has examined the dynamics of liquidity in a network economy, with a particular focus on the composition of short-term assets and liabilities. We have underlined the high importance of sufficient liquidity for firms to meet their short-term obligations, and address the effects of unforeseen factors in the US economy. Our primary aim is to investigate the dynamic components of liquidity movement within a network economy where firms engage in active trading and possess short-term assets and liabilities. We also attempt to examine the contribution of each shock in explaining the variations of endogenous variables.

To address the research objectives of this study, the study looks closely into the origins of aggregate fluctuations within a network economy that may arise from liquidity changes and related forces. We focus on analyzing the liquidity dynamics in the U.S. economy using the SVAR model. The SVAR model serves as a powerful analytical framework widely utilized in macroeconomic research to investigate the intricate interactions between different variables, explore the joint dynamics of multiple variables within a system, and estimate the effects of unexpected exogenous shocks on the variables under study.

In pursuit of this objective, we use the variables repo rates, GDP, quick ratio, and the network measure of receivables/payables accounts, and employ the Structural Vector Autoregression (SVAR) model to investigate the relationships and interactions between liquidity and related endogenous variables and identifying the origins of aggregate fluctuations arising from liquidity shortages. we begin by identifying the relevant innovations within the variables of interest and describe the response of the system to two standard deviation shocks, analyzing the propagation mechanisms of shocks through the Impulse Response Functions (IRFs). By utilizing the IRF analysis, the research quantifies the short-term effects of liquidity shocks on interest rates, GDP, quick ratio, and the network measure. The IRF analysis allows for an examination of how the system responds to two standard deviation sudden changes in liquidity-related variables, providing valuable information on the transmission channels and persistence of liquidity shocks.

The study also assesses the importance of each shock in explaining the variations observed in the endogenous variables by decomposing the Forecast Error Variance (FEV) and determining the proportion of shocks throughout the entire system. By quantifying the contribution of innovations to the overall forecast errors, this analysis will shed light on the relative importance of liquidity dynamics in shaping the behavior of markets. Overall, these research questions aim to deepen our understanding of liquidity dynamics and their implications for an economy, contributing to the body of knowledge on the subject and informing policymakers and market participants about the importance of maintaining adequate liquidity levels.

Furthermore, the chapter incorporates additional exogenous variables that are known to be influential drivers of liquidity in the economy to improve the accuracy of the impulse response functions and forecast error variance decomposition. These variables include the Federal Funds Rate (FFR), Consumer Price Index (CPI), monetary supply, and the U.S. dollar exchange rate. The Federal Funds Rate represents the interest rate at which depository institutions lend reserve balances to other institutions overnight. The Consumer Price Index measures changes in the price level of consumer goods and services. The monetary supply and the U.S. dollar exchange rate capture the liquidity in circulation in the entire economy.

It is important to note that the analysis of shocks is not a straightforward task, and researchers must carefully consider the assumptions and limitations of the model when interpreting the results. The reliability of findings has further been validated reliability through robustness checks employing different identification methods and different network measures. The study applies both AB-model and B-model identification to incorporate the contemporaneous and non-contemporaneous effects. Furthermore, in our analysis, we employ different network centrality measures and moments of degree distribution to capture the significance of different nodes and linkages within the network. This approach enables us to explore the importance of specific firms and their interconnectedness in the network economy.

The findings of this research are extensive. However, here we only highlight some of the

findings. The chapter shows that with two standard deviation shocks to our system of equations, the largest responses in the whole system are mainly for the past values of the endogenous variables themselves. The responses are captured respectively by the quick ratio and the network effect with 0.2 and 0.15%. The GDP and the repo rate go after, both with a 0.1 percent change. However, the GDP by far is the most volatile variable and is the last variable among all the endogenous variables that the fluctuations fade away. The FEVD then underlines the role of the network and the quick ratio fluctuations among the liquidity-related variables. The highest variations between the self-innovation variables are accounted for by the network effect, quick ratio, GDP, and repo rate, with averages of approximately 93%, 83%, 81%, and 64%, respectively. Regarding non-self-innovations, the highest proportion of variation is observed in network data and quick ratios. Regarding the second-highest rank in system fluctuations, the baseline scenario shows a high proportion of fluctuations in the repo rate derived from the network data. The findings also demonstrate the effects of quick ratio on GDP fluctuations.

In conclusion, comprehending the dynamics of liquidity and the complex nature of liquidity in financial and monetary markets is crucial for improving financial stability and sustainable economic growth. This research underscores the importance of comprehending liquidity dynamics and highlights avenues for further investigation. By addressing these challenges and building upon this knowledge, we can continue to promote resilient and efficient financial systems that contribute to the overall prosperity and well-being of society. Future research should initially focus on establishing the theoretical model of the study. Subsequently, it should aim to enhance this approach by refining the identification of the SVAR model and integrating the exogenous variables of the model as endogenous variables.

Chapter 5

Contributions and Concluding Remarks

This thesis aims to improve our understanding of liquidity at both a national and international level. This research contributes to the ongoing literature to monitor and manage liquidity risks by examining the stability of the system, exploring the vulnerabilities, and identifying the channels of risk that have the potential to destabilize the system. The analysis conducted in this study uses financial network tools and measures to provide valuable insights for policymakers, regulators, and researchers, finally aiming to improve the resilience of the financial system.

The second and third chapters of this thesis employ the network approach to assess systemic risk and financial contagion in cross-border banking system. The second chapter analyzes the properties and stability of the global banking system for 19 reporting BIS countries and provides an empirical analysis of the cross-border banking system network and its systemic risk based on the eigen-pair method for the time span of 2005 to 2020. The eigen-pair approach captures the systemic risk more precisely compared to other market price-based methods and provides early signals over the spread of contagion once the systemic risk index exceeds the threshold of 1 (similar to the R number in epidemiology (Van den Driessche, 2017)). Our results show that although the risk in the cross-border banking system is decreasing after the 2008 crisis,

the system stay unstable throughout the whole sample period, even after Basel III has been introduced by the Basel Committee.

The third chapter contributes to the existing literature by extending the eigen-pair network method by adding the liquid assets and short-term liabilities and taking the liquidity risk into account. We also show that the liquidity effect aggravates the whole system risk and increases the instability of the cross-border banking system through the contagion effect. We assess that liquid assets can change the ranking of the systemically important banking systems as well as systemically vulnerable countries for the sample period. Given that the banking systems have liquid assets to compensate for their loss, the US, UK, Japan, Australia, and Turkey are the top systemically important banking system while without the net liquid assets, the top 5 systemic important countries are the US, UK, Spain, France, and Germany, respectively. Regarding the systemically vulnerable banking system, considering the liquidity, the average left eigenvector centralities show that the top vulnerable banking systems are Sweden, Switzerland, Italy, Germany, and Japan. However, given solvency risk, the top 5 systemic vulnerable countries are Japan, Spain, Switzerland, Germany, and France, respectively.

The fourth chapter has mainly examined the dynamics of liquidity in a network economy, with a particular focus on the composition of short-term assets and liabilities. In pursuit of this objective, we use the four main liquidity-related variables in an economy including the repo rates, GDP, quick ratio, and the network metrics of receivables/payables accounts, and apply the Structural Vector Autoregression (SVAR) model to analyze the relationships and interactions between liquidity measures and other endogenous variables. we start by identifying the relevant innovations within the variables of interest and describe the responses of the system to each structural innovation and by analyzing the propagation mechanisms of shocks through the Impulse Response Function (IRF). The IRF analysis seeks to quantify the short-term effects of liquidity shocks on interest rates, GDP, quick ratio, and the network measure to examine how the system responds to sudden changes in liquidity and provides valuable information not only on the transmission channels but on the persistence of liquidity shocks in the system. We

also investigate the importance of each shock in explaining the changes and variations observed from the other endogenous variables by decomposing the Forecast Error Variance (FEV) and specifying the proportion of shocks throughout the entire system.

The fourth chapter's results reveal that the economy is highly responsive to past values of the endogenous variables. The responses are captured by the quick ratio and the network effect with 0.2 and 0.15%, respectively. The GDP and repo rate also show significant responses with a 0.1% change. The GDP is the most volatile variable and shows longer fluctuations compared to others. The study further highlights the role of network and the quick ratio fluctuations among the liquidity-related variables. The highest variations between the self-innovation variables are accounted for by the network effect, quick ratio, GDP, and repo rate, with averages of approximately 93%, 83%, 81%, and 64%, respectively. Regarding non-self-innovations, the highest proportion of variation is observed in network data and quick ratios. Regarding the second-highest rank in system fluctuations, the baseline scenario shows a high proportion of fluctuations in the repo rate derived from the network data. The findings also demonstrate the effects of quick ratio on GDP fluctuations. By providing the quantitative contribution of innovations to the overall forecast errors, this analysis will shed light on the relative importance of liquidity dynamics in generating the fluctuations of markets.

Overall, this thesis aims to deepen our understanding of liquidity and its dynamic at a national and international level using financial network models. We introduce a new network-based systemic risk index and identify the systemic important and vulnerable components in the cross-border banking system. We also investigate the dynamics of liquidity in a US economy and show the contributions of corresponding shocks to the variables under study. Finally, we contribute to the body of knowledge by highlighting the significant role of maintaining adequate liquidity levels in the market.

Appendix A

Complementary Materials for Solvency and Liquidity Analysis in Cross-border Banking System

A.1 Annex A - Instruction for cross border data using BIS Consolidated Banking Statistics (CBS)

This section first explains the dynamic of the system based on the Markose et al. (2021) by introducing the stylized balance sheet of a bank and then fitting the framework with the cross-border banking system data using BIS consolidated banking statistics.

A. A stylized balance sheet for a cross-border bank:

The departure point to analyse the dynamic of the cross-border banking system in Equation 2.5 is to understand the financial position of a bank based on its balance sheet structure. A balance sheet of a bank contains information on total assets and total liabilities, and the difference between them represents the equity capital as follows,

$$A_{b_i 0} - L_{b_i 0} = C_{b_i 0} \tag{A.1}$$

where A_{b_i0} and L_{b_i0} respectively are the total assets and total liabilities for the bank i at an initial time, and C_{b_i0} denotes equity capital for the bank b_i at an initial time 0. As the balance sheet for a cross-border bank generally reflects the interbank as well as non-interbank system, the equation can also be shown in the following form,

$$\sum_{b_j}(X^D_{b_jb_i} - X^D_{b_ib_j}) + A^{\#D}_{b_i0} - L^{\#D}_{b_i0} = C_{b_i0} \tag{A.2}$$

where $X_{b_jb_i}$ denotes the liabilities of bank b_j to its counterparty b_i, that is b_i's assets and vice versa, and $\sum_{b_j}(X^D_{b_jb_i} - X^D_{b_ib_j})$ represents the interbank part of the balance sheet. $A^{\#D}_{b_i0}$ and $L^{\#D}_{b_i0}$ show the non-interbank (external) assets and liabilities. Since our aim is to analyze the cross-border flows in the banking system, we assume that the depletion of equity capital arises only from the term $\sum_{b_j}(X^D_{b_jb_i} - X^D_{b_ib_j})$, which can reflect the cross border interbank failure of net debtors of bank b_i.[1] Thus, we can refer $\sum_{b_j}(X^D_{b_jb_i} - X^D_{b_ib_j})^+ u_{b_jt}$ in Equation 2.5 to total losses from the net debtor counterparties of bank b_i with the rate of defaults of counterparty b_j, u_{b_jt}.

$$C_{b_it+1} = C_{b_i0} - \sum_{b_j}(X^D_{b_jb_i} - X^D_{b_ib_j})^+ u_{b_jt} - (1-\rho)(C_{b_i0} - C_{b_it}) \tag{A.3}$$

where $(C_{b_i0} - C_{b_it})$ denote the cumulative loss of capital until time t and thus $(1-\rho)(C_{b_i0} - C_{b_it})$ shows the residual losses that are not balanced by the capital buffer since the regulatory requires banks not to exceed total losses at any time t more than a threshold ρ of initial capital. Therefore, the rate of default of banking system b_i at time $t+1$, u_{b_it+1} can be written using the cumulative rate of capital depletion that can be driven by subtracting C_{b_it+1} from C_{b_i0} and divided by C_{b_i0}, and we have,

$$u_{b_it+1} = \frac{C_{b_i0} - C_{b_it+1}}{C_{b_i0}} = \sum_{b_j}\frac{(x_{b_ib_j} - x_{b_jb_i})^+}{C_{b_i0}} u_{b_jt} + (1-\rho)u_{b_it} \tag{A.4}$$

[1] Another assumption is that there is no losses and no capitalization in non-interbank balance sheet for banking system b_i.

This exhibits the dynamics of Equation 2.5 for the rates of failing banks from a loss of capital stemming from the failure rates of counterparties in the banking system. It is also noteworthy to mention that when losses arise from a subset of the balance sheet, a pro-rata adjustment of the data is required to model this subset of the balance sheet. Otherwise, the contagion effect can be significantly underrated. The adjustment steps are explained in Section A.2.

B. Applying cross-border bank data using BIS Consolidated Banking Statistics (CBS):

So far, the dynamic of the system is explained without taking the cross-border banking system into account. Now, we need to fit the framework in Subsection 2.3 with the *cross border bank data*, which relies on banking sector breakdown.[2] Note, since the BIS consolidated data are reported at an aggregate level (banking sector) rather than individual banks, the netting is derived at the aggregate banking system level. The CBS captures the global consolidated positions of international banks headquartered in reporting countries. Thus, it measures the financial activity of the global banking system from a nationality point of view, emphasizing the sovereign where the banking sector's parent is headquartered. In order to exhibit how the data applied to Equation 2.5, the stylized balance sheet of a banking system has been shown as follows:

$$\sum_{j} X^{F}_{B_j b_i^R} + A^{\#DF}_{b_i^R} - \sum_{j} X^{F}_{b_i^R B_j} - L^{\#DF}_{b_i^R} = C_{b_i^R} \tag{A.5}$$

[2]Note, the reporting national banking system are the United States, United Kingdom, Japan, Switzerland, Austria, Belgium, Finland, France, Germany, the Netherlands, Greece, Italy, Ireland, Portugal, and Spain, Australia, Canada, Sweden, and Turkey. However, at the beginning of our sample, in 2006:Q1, the sectoral breakdown for foreign claims is reported only for 10 main banking systems (out of 19 countries), i.e. Australia, Belgium, France, Ireland, Japan, Portugal, Sweden, Switzerland, UK, and the US. Italy, Canada, and Finland started reporting foreign claims in 2007:Q3, 2008:Q3, and 2010:Q2, respectively. Germany and Spain provided the data from 2010:Q4. Also, Austria and Greece are available only from 2013:Q4. The Netherlands and Turkey do not report any foreign claims on their reporting counterparties at all. The process of constructing the proxy for missing data is explained in Annex A.2.

Here, we denote b_i^R as the BIS reporting bank i with the foreign claims on the counterparty bank j, and b_i^{NR} declares the non-reporting banks with no foreign claims. However, some of these banking systems have liabilities to other reporting countries. Hence, we define $B_i = \sum b_i^R + \sum b_i^{NR}$ as the entire banking system i. In the LHS, $\sum_j X^F_{B_j b_i^R}$ is the assets (claims) of banking system b_i^R on banking system B_j, and $\sum_j X^F_{b_i^R B_j}$ is the liabilities of bank b_i^R owed to bank B_j. F also stands for foreign status. Also, $A^{\#DF}_{b_i^R}$ and $L^{\#DF}_{b_i^R}$ denote domestic interbank and non-interbank domestic and foreign assets/liabilities of banking system b_i^R of country i, respectively. In the RHS, $C_{b_i^R}$ is the capital of cross-border bank b_i^R in country i.

We then obtain the total capital of BIS reporting banking system i by aggregating over all banks in the country i and netting with liabilities of other counterparties banks j,

$$\sum_{b^R}\sum_{j\neq i}(X^F_{B_j b_i^R} - X^F_{b_i^R B_j}) + \sum_{b^R} A^{\#DF}_{b_i^R} - \sum_{b^R} L^{\#DF}_{b_i^R} = \sum_{b^R} C_{b_i^R} \tag{A.6}$$

where $\sum_{b^R} C_{b_i^R}$ is the total capital reporting banks in BIS country i, $\sum_{b^R} X^F_{B_j b_i^R}$ denotes foreign claims of BIS reporting banks of sovereign i on the counterparty banking system B_j, which correspond to element X_{ji} in Equation 2.5. Here, the term $\sum_{b^R} X^F_{b_i^R B_j^R}$, which is the liability side of BIS banks, is not available. We then create a proxy by using the share of total sectoral liabilities of counterparty country j and the sum of foreign liabilities of counterparty j (see the details in Annex A.2).

A.2 Annex B - Adjustment of the data for cross-border banking system network:

The discussion in the methodology section requires some adjustments presented in the following 3 steps to build the stability matrix and then study the dynamics of the model for the cross-border banking network based on Tier 1 capital and the BIS data.

Step 1: *Banking system claims data for the BIS reporting countries:*

As the banking sector breakdown has not been reported for some BIS reporting countries, a proxy is built for only the non-reporting banking system by adjusting foreign claims for each banking system i on all the sectors, S, of counterparty j, viz. $\sum_{b^R} X^F_{S_j b_i^R}$, in order to capture only foreign claims of the baking sector, B_j, of country j, $\sum_{b^R} X^F_{B_j b_i^R}$. The adjustment ratio $\frac{\sum_i X_{B_j B_i^R}}{\sum_i X_{S_j b_i^R}}$ is applied to scale down the sectoral foreign claims $\sum_{b^R} X^F_{S_j b_i^R}$ since it measures the share of total sectoral liabilities of country j. Here, $\sum_i X_{B_j B_i^R}$ is the total liabilities of banking sector j, and $\sum_i X_{S_j b_i^R}$ denotes total liabilities of sectors j.

Step 2: *Adjustment of cross-border banking system exposures:*

As the Tier 1 capital, which is reported in IMF database[3], is based on the consolidated balance sheet of banks, so it is consistent with the BIS consolidated statistics. Nevertheless, the regulatory capital requirement is required to be adjusted and restricted to the cross-border assets and liabilities of reporting banking system. Here, the total amount of Tier 1 capital for the cross-border reporting banking system is needed to be adjusted by the ratio $\frac{\sum_{b^R}\sum_{j\neq i} X^F_{B_j b_i^R}}{\sum_{b^R}\sum_{j\neq i} X^F_{S_j b_i^R}}$ taken from Step 1 so that we can specify what absolute losses can be taken before a banking system can be considered under stress.

Step 3: *Absolute Tier 1 capital loss thresholds based on Basel* $\frac{CAR}{RWA}$*:*

The role of *capital threshold* is crucial in specifying the tipping point for the whole network. That is, the degree losses of capital that can be held in the balance sheet before the banking system become solvent. As discussed in the methodology Section 2.3 Equation 2.5, the Tier 1 capital for the cross-border banking systems converts to an *absolute Tier 1 capital loss threshold* based on the *capital adequacy ratio*. This allows us not only to compare the permissible capital loss between the banking sector but also to explain the dynamics of Equation 2.5 on the basis of the tipping point 1 in Equation 2.8.

[3]The IMF data can be found in https://data.imf.org.

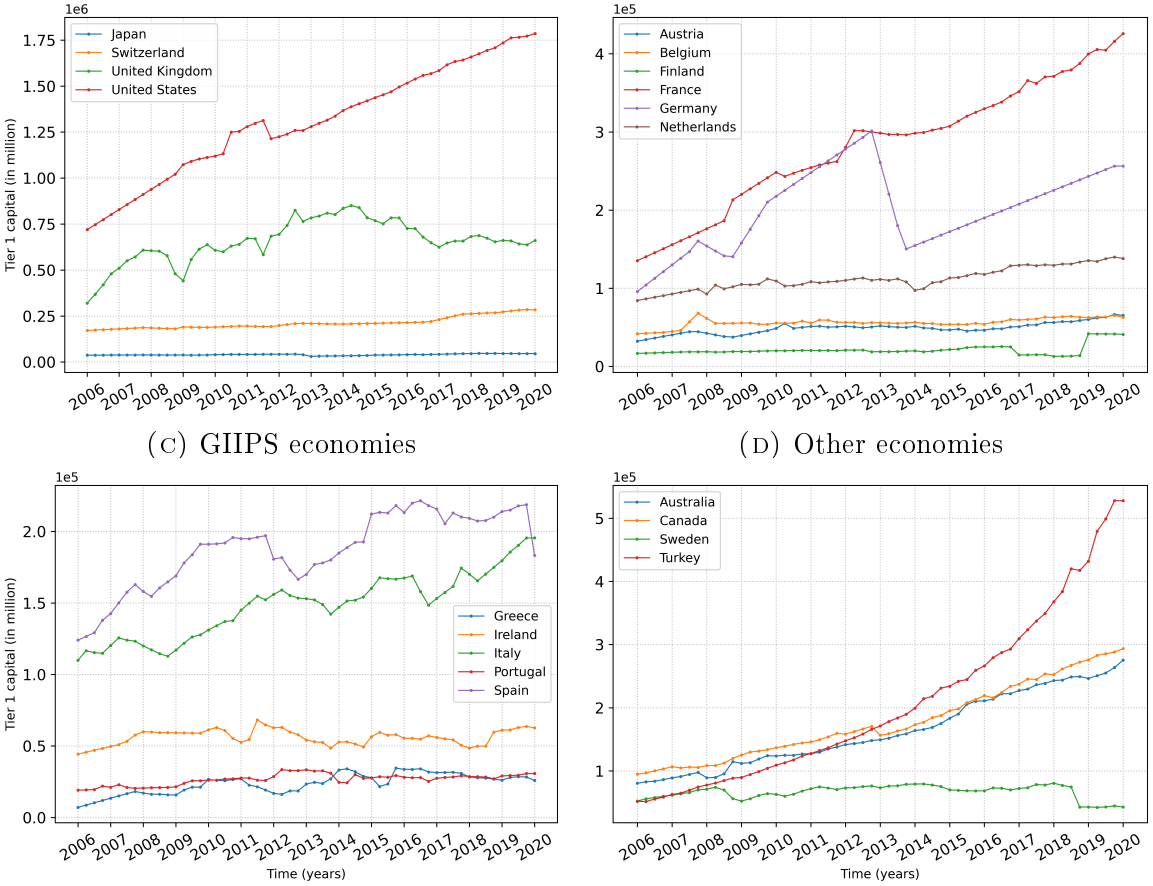
A.3 Annex C - Tier 1 capital

Figure A.1 plots the original raw Tier 1 capital before the adjustments in Section A.2 implemented. The table exhibits the Tier 1 capital for different categories within the sample period 2005 to 2020. Figure A.2 later on shows the growth of aggregated Tier 1 capital in the global banking system throughout the period 2005:Q1 and 2020:Q1.

FIGURE A.1: Tier 1 capital time series

(A) Core economies

(B) EU non-GIIPS economies



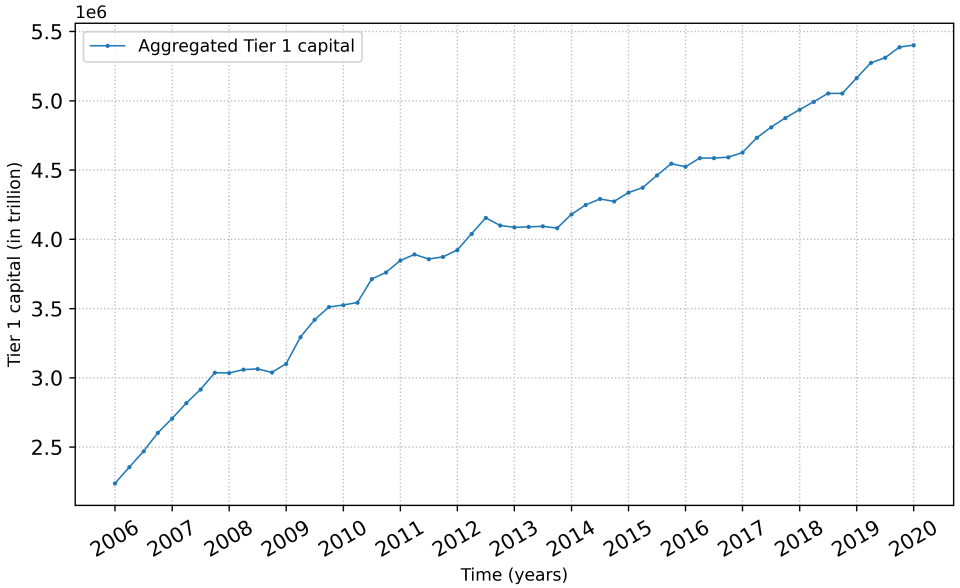
(C) GIIPS economies

(D) Other economies

Note: Figure shows quarterly Tier 1 Capital in million US dollars for BIS reporting Banking systems between 2005:Q1 and 2020:Q1. "e" means exponent and 1e5 and 1e6 are the scientific notation which means 10 to the power of 5 and 6, respectively.

Data source: plotted by author using IMF database.

FIGURE A.2: Aggregated Tier 1 capital time series



Note: The Figure exhibits the aggregated Tier 1 capital time series in trillion dollars from 2005:Q1 to 2020:Q1 for the BIS reporting countries.

Data source: Calculated and plotted by the author using IMF database.

The adjustment ratios that explained in Annex A.2 and is used to restrict the data to only cross-border headquartered banking system shown in Figure A.3. The figure shows the ratios used to adjust Tier 1 capital to BIS reporting banking system.

FIGURE A.3: Adjustment ratios

	2006-Q1	2006-Q2	2006-Q3	2006-Q4	2007-Q1	2007-Q2	2007-Q3	2007-Q4	2008-Q1	2008-Q2	2008-Q3	2008-Q4	2009-Q1	2009-Q2	2009-Q3	2009-Q4	2010-Q1	2010-Q2	2010-Q3	2010-Q4	2011-Q1	2011-Q2
Australia	0.34	0.32	0.32	0.29	0.28	0.26	0.28	0.28	0.29	0.28	0.26	0.29	0.25	0.27	0.25	0.27	0.28	0.29	0.28	0.29	0.29	0.30
Austria	0.44	0.43	0.42	0.37	0.39	0.39	0.31	0.31	0.33	0.34	0.34	0.30	0.25	0.23	0.21	0.21	0.22	0.27	0.21	0.38	0.38	0.36
Belgium	0.63	0.62	0.67	0.63	0.67	0.64	0.60	0.66	0.68	0.65	0.62	0.54	0.52	0.52	0.45	0.30	0.28	0.29	0.35	0.27	0.25	0.19
Canada	0.28	0.27	0.27	0.28	0.27	0.25	0.23	0.25	0.28	0.25	0.27	0.25	0.24	0.20	0.21	0.21	0.21	0.21	0.19	0.20	0.20	0.19
Finland	0.29	0.31	0.29	0.28	0.15	0.15	0.13	0.17	0.15	0.15	0.16	0.14	0.15	0.17	0.13	0.19	0.13	0.18	0.13	0.23	0.18	0.18
France	0.47	0.46	0.46	0.46	0.50	0.50	0.49	0.48	0.50	0.50	0.47	0.46	0.43	0.43	0.43	0.46	0.49	0.50	0.46	0.49	0.48	0.49
Germany	0.45	0.43	0.43	0.46	0.42	0.42	0.38	0.38	0.42	0.40	0.35	0.32	0.34	0.32	0.33	0.34	0.36	0.37	0.33	0.30	0.28	0.29
Greece	0.13	0.15	0.15	0.10	0.11	0.12	0.11	0.14	0.17	0.16	0.15	0.10	0.11	0.11	0.11	0.12	0.08	0.06	0.06	0.08	0.08	0.07
Ireland	0.35	0.33	0.33	0.32	0.33	0.33	0.34	0.36	0.37	0.37	0.33	0.25	0.21	0.21	0.21	0.23	0.25	0.25	0.22	0.18	0.17	0.17
Italy	0.21	0.20	0.20	0.18	0.19	0.19	0.19	0.18	0.18	0.19	0.16	0.14	0.14	0.13	0.12	0.12	0.12	0.13	0.12	0.17	0.18	0.17
Japan	0.24	0.26	0.22	0.21	0.21	0.21	0.18	0.18	0.20	0.18	0.19	0.20	0.25	0.25	0.29	0.30	0.30	0.33	0.34	0.34	0.33	0.33
Netherlands	0.35	0.32	0.36	0.37	0.35	0.36	0.36	0.41	0.40	0.36	0.33	0.31	0.27	0.28	0.28	0.27	0.28	0.24	0.23	0.25	0.26	0.27
Portugal	0.30	0.27	0.27	0.25	0.30	0.32	0.30	0.28	0.25	0.25	0.20	0.19	0.15	0.14	0.15	0.15	0.16	0.17	0.15	0.21	0.20	0.17
Spain	0.35	0.32	0.31	0.27	0.30	0.29	0.30	0.32	0.33	0.32	0.31	0.31	0.26	0.26	0.25	0.26	0.29	0.30	0.26	0.31	0.29	0.30
Sweden	0.49	0.48	0.46	0.38	0.44	0.41	0.36	0.39	0.46	0.42	0.38	0.38	0.32	0.32	0.33	0.33	0.33	0.34	0.34	0.41	0.43	0.44
Switzerland	0.59	0.58	0.61	0.56	0.58	0.59	0.54	0.50	0.51	0.53	0.48	0.46	0.49	0.46	0.44	0.46	0.46	0.46	0.38	0.36	0.33	0.33
Turkey	0.22	0.21	0.23	0.16	0.29	0.28	0.27	0.31	0.44	0.44	0.26	0.31	0.25	0.26	0.26	0.26	0.26	0.25	0.24	0.31	0.30	0.30
United Kingdom	0.39	0.36	0.38	0.35	0.40	0.39	0.40	0.38	0.40	0.41	0.36	0.35	0.31	0.30	0.29	0.29	0.30	0.30	0.28	0.29	0.29	0.28
United States	0.20	0.19	0.19	0.19	0.19	0.19	0.20	0.21	0.29	0.30	0.21	0.20	0.18	0.18	0.16	0.16	0.15	0.15	0.15	0.16	0.16	0.15

	2010-Q3	2010-Q4	2011-Q1	2011-Q2	2011-Q3	2011-Q4	2012-Q1	2012-Q2	2012-Q3	2012-Q4	2013-Q1	2013-Q2	2013-Q3	2013-Q4	2014-Q1	2014-Q2	2014-Q3	2014-Q4
Australia	0.28	0.29	0.29	0.30	0.32	0.30	0.28	0.30	0.30	0.30	0.29	0.32	0.31	0.32	0.31	0.31	0.32	0.31
Austria	0.21	0.38	0.38	0.36	0.36	0.34	0.34	0.32	0.32	0.31	0.31	0.31	0.29	0.41	0.41	0.39	0.27	0.22
Belgium	0.35	0.27	0.25	0.19	0.16	0.15	0.16	0.14	0.15	0.14	0.15	0.13	0.13	0.12	0.12	0.11	0.14	0.12
Canada	0.19	0.20	0.20	0.19	0.19	0.21	0.21	0.20	0.21	0.24	0.23	0.23	0.22	0.24	0.22	0.24	0.25	0.25
Finland	0.13	0.23	0.18	0.18	0.20	0.25	0.26	0.23	0.22	0.24	0.20	0.20	0.18	0.17	0.15	0.17	0.17	0.15
France	0.46	0.49	0.48	0.49	0.49	0.44	0.42	0.42	0.43	0.40	0.41	0.39	0.39	0.37	0.37	0.35	0.35	0.35
Germany	0.33	0.30	0.28	0.29	0.27	0.28	0.25	0.22	0.22	0.21	0.22	0.21	0.21	0.21	0.24	0.25	0.25	0.23
Greece	0.06	0.08	0.08	0.07	0.05	0.04	0.03	0.02	0.02	0.07	0.30	0.53	0.61	0.58	0.59	0.64	0.61	0.61
Ireland	0.22	0.18	0.17	0.17	0.17	0.16	0.15	0.15	0.15	0.16	0.16	0.16	0.14	0.16	0.15	0.15	0.15	0.15
Italy	0.12	0.17	0.18	0.17	0.16	0.15	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.14	0.15	0.15	0.15	0.14
Japan	0.34	0.34	0.33	0.33	0.32	0.30	0.33	0.35	0.34	0.35	0.36	0.37	0.32	0.30	0.26	0.26	0.25	0.25
Netherlands	0.23	0.25	0.26	0.27	0.25	0.23	0.23	0.24	0.26	0.24	0.24	0.23	0.24	0.23	0.25	0.26	0.26	0.25
Portugal	0.15	0.21	0.20	0.17	0.16	0.16	0.14	0.12	0.12	0.12	0.12	0.12	0.10	0.12	0.14	0.14	0.13	0.11
Spain	0.26	0.31	0.29	0.30	0.30	0.27	0.25	0.25	0.26	0.24	0.27	0.29	0.31	0.32	0.33	0.32	0.32	0.32
Sweden	0.34	0.41	0.43	0.44	0.45	0.47	0.51	0.50	0.54	0.51	0.51	0.54	0.54	0.53	0.55	0.54	0.55	0.51
Switzerland	0.38	0.36	0.33	0.33	0.32	0.33	0.28	0.30	0.30	0.26	0.25	0.27	0.22	0.20	0.21	0.21	0.19	0.20
Turkey	0.24	0.31	0.30	0.30	0.31	0.32	0.30	0.30	0.28	0.29	0.32	0.34	0.35	0.29	0.33	0.32	0.35	0.31
United Kingdom	0.28	0.29	0.29	0.28	0.28	0.25	0.25	0.25	0.26	0.26	0.26	0.26	0.25	0.25	0.27	0.26	0.27	0.23
United States	0.15	0.16	0.16	0.15	0.15	0.14	0.14	0.13	0.13	0.13	0.13	0.12	0.12	0.09	0.11	0.12	0.10	0.10

	2015-Q1	2015-Q2	2015-Q3	2015-Q4	2016-Q1	2016-Q2	2016-Q3	2016-Q4	2017-Q1	2017-Q2	2017-Q3	2017-Q4	2018-Q1	2018-Q2	2018-Q3	2018-Q4	2019-Q1	2019-Q2	2019-Q3	2019-Q4	2020-Q1
Australia	0.30	0.30	0.31	0.29	0.28	0.28	0.27	0.26	0.24	0.22	0.22	0.22	0.22	0.22	0.20	0.22	0.20	0.20	0.17	0.20	0.22
Austria	0.22	0.20	0.21	0.19	0.18	0.18	0.16	0.16	0.17	0.16	0.16	0.15	0.19	0.18	0.18	0.17	0.18	0.18	0.17	0.18	0.18
Belgium	0.13	0.12	0.11	0.10	0.12	0.11	0.11	0.12	0.12	0.13	0.11	0.11	0.12	0.12	0.12	0.10	0.10	0.10	0.11	0.09	0.11
Canada	0.25	0.25	0.27	0.28	0.28	0.28	0.28	0.29	0.28	0.28	0.28	0.27	0.28	0.30	0.30	0.29	0.28	0.28	0.27	0.28	0.28
Finland	0.16	0.16	0.16	0.14	0.12	0.11	0.10	0.13	0.10	0.10	0.08	0.09	0.09	0.09	0.09	0.21	0.25	0.24	0.22	0.25	0.24
France	0.34	0.33	0.35	0.33	0.33	0.32	0.29	0.28	0.27	0.30	0.30	0.27	0.29	0.30	0.29	0.26	0.31	0.32	0.31	0.31	0.32
Germany	0.23	0.22	0.23	0.21	0.21	0.21	0.20	0.18	0.17	0.17	0.16	0.16	0.16	0.15	0.16	0.15	0.15	0.15	0.14	0.16	0.17
Greece	0.09	0.08	0.08	0.29	0.48	0.53	0.58	0.60	0.61	0.60	0.61	0.57	0.59	0.64	0.63	0.69	0.63	0.59	0.52	0.54	0.51
Ireland	0.14	0.15	0.13	0.12	0.12	0.13	0.10	0.10	0.09	0.10	0.09	0.08	0.08	0.08	0.08	0.06	0.06	0.06	0.07	0.07	0.07
Italy	0.15	0.15	0.14	0.15	0.14	0.15	0.13	0.13	0.12	0.11	0.11	0.10	0.11	0.12	0.13	0.10	0.10	0.09	0.09	0.10	0.10
Japan	0.25	0.25	0.24	0.26	0.26	0.26	0.27	0.31	0.29	0.28	0.27	0.28	0.27	0.26	0.24	0.25	0.24	0.21	0.21	0.25	0.20
Netherlands	0.25	0.25	0.25	0.23	0.24	0.22	0.21	0.21	0.21	0.19	0.20	0.19	0.21	0.21	0.21	0.22	0.23	0.23	0.23	0.21	0.21
Portugal	0.10	0.12	0.11	0.09	0.09	0.09	0.09	0.09	0.08	0.09	0.07	0.07	0.07	0.08	0.08	0.07	0.06	0.06	0.06	0.07	0.07
Spain	0.33	0.29	0.29	0.27	0.26	0.24	0.24	0.24	0.22	0.22	0.23	0.22	0.21	0.19	0.20	0.19	0.18	0.17	0.15	0.18	0.17
Sweden	0.52	0.54	0.53	0.51	0.51	0.50	0.50	0.48	0.51	0.49	0.50	0.48	0.50	0.49	0.47	0.59	0.60	0.61	0.58	0.60	0.62
Switzerland	0.21	0.21	0.20	0.19	0.21	0.21	0.19	0.18	0.13	0.13	0.12	0.12	0.13	0.15	0.15	0.16	0.16	0.16	0.13	0.14	0.15
Turkey	0.31	0.29	0.22	0.20	0.19	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.22	0.22	0.22	0.19	0.18	0.18	0.18	0.16	0.15
United Kingdom	0.24	0.21	0.22	0.20	0.21	0.21	0.21	0.19	0.19	0.20	0.20	0.19	0.21	0.22	0.21	0.19	0.19	0.20	0.20	0.20	0.21
United States	0.10	0.09	0.10	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.06	0.06

Note: The Table exhibits adjustment ratio quarterly from 2005:Q1 to 2020:Q1 for the BIS reporting countries.

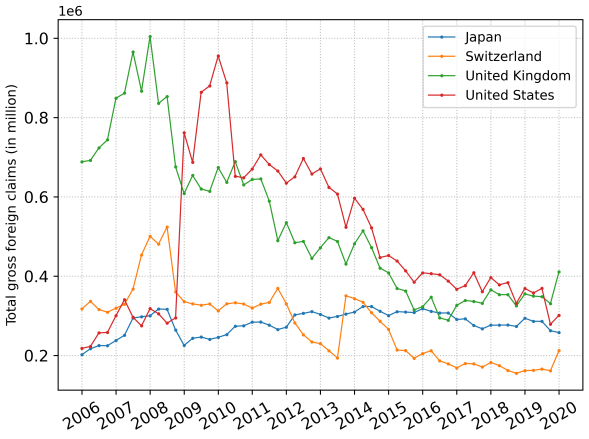
Data source: Calculated by the author using BIS database.

A.4 Annex D - Total gross foreign claims/liabilities

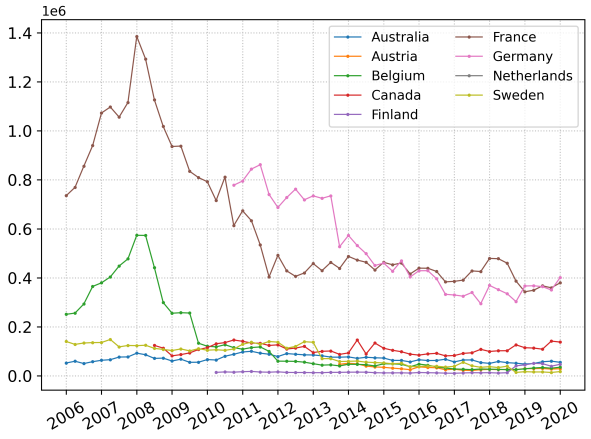
Figure A.4 and Figure A.5 respectively exhibit the total gross foreign claims and liabilities in million dollars for all BIS reporting banking systems from 2005:Q1 to 2020:Q1.

FIGURE A.4: Total gross foreign claims

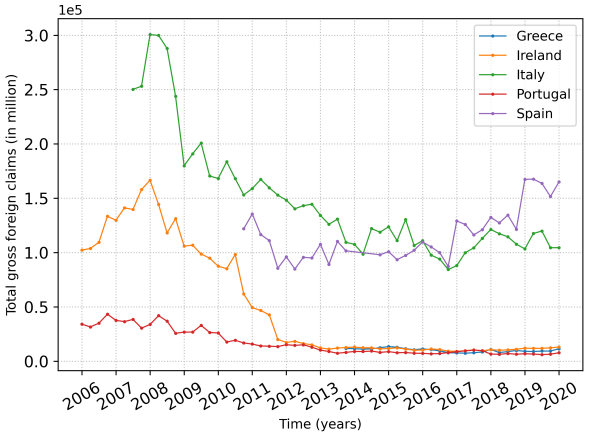
(A) Core economies



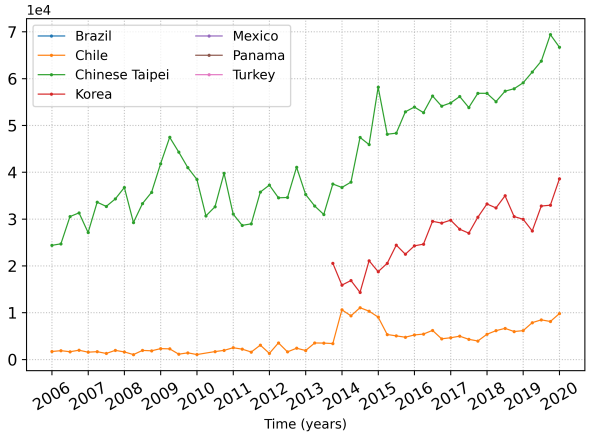
(B) Developed economies



(C) GIIPS economies



(D) Emerging economies



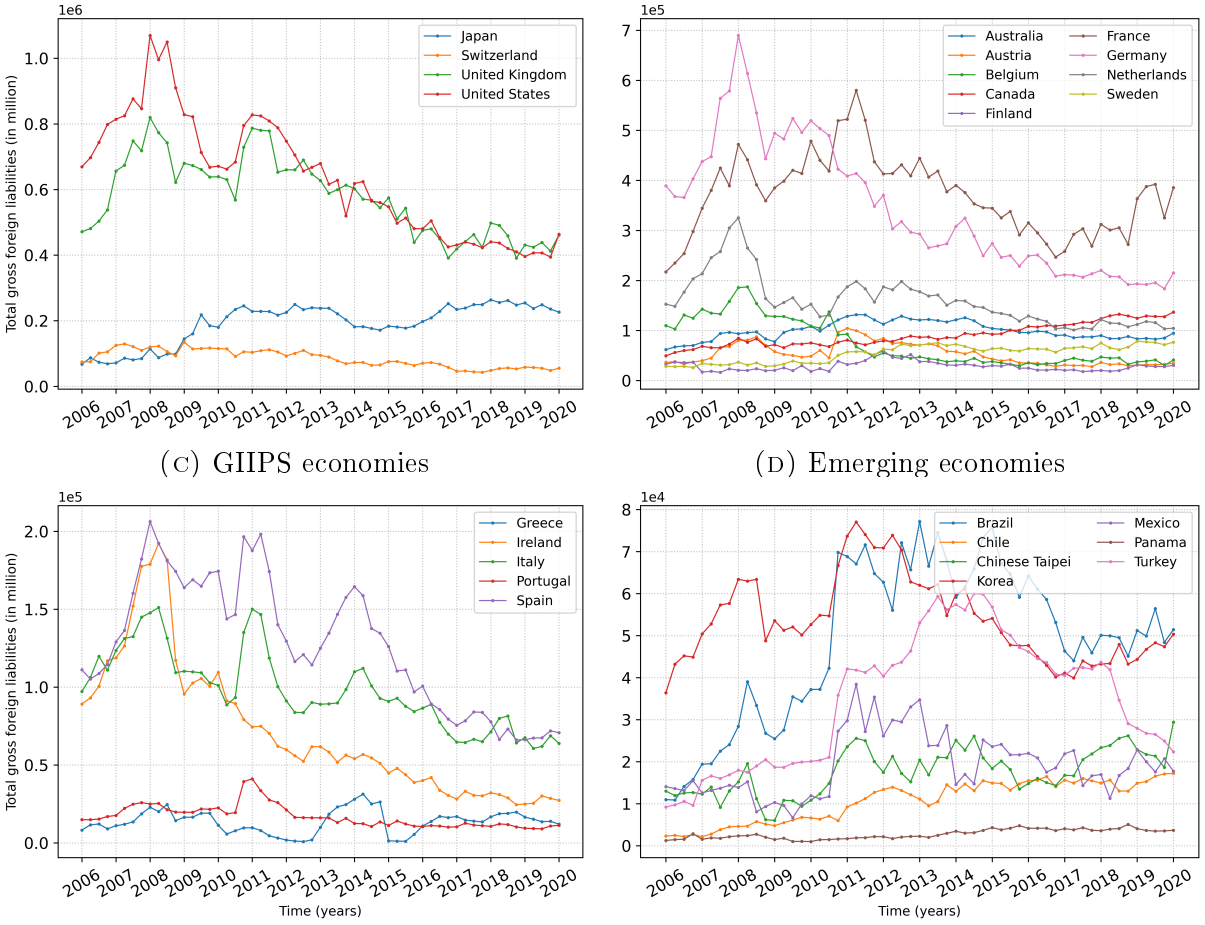
Note: The Figure represents the total gross foreign claims in million dollars for the BIS reporting countries from 2005:Q1 to 2020:Q1. "e" means exponent, and also 1e5 and 1e6 are the scientific notation which means 10 to the power of 5 and 6, respectively.

Data source: BIS consolidated banking system statistics.

FIGURE A.5: Total gross foreign liabilities

(A) Core economies

(B) Developed economies



(C) GIIPS economies

(D) Emerging economies

Note: The Figure shows the total gross foreign liabilities in million dollars for the BIS reporting countries from 2005:Q1 to 2020:Q1. "e" means exponent, and also 1e6 is the scientific notation which mean 10 to the power of 6.

Data source: BIS consolidated banking system statistics.

A.5 Annex E - Network statistics

As a starting point to characterize the network, there are different network statistics that can specify the number and strength of the edges between each node as well as the dynamic of the network over time.

Network Degree: *Degree* of network denotes the number of links that connect each node (i.e., banking system) to its counterparties. *Out-degree* and *in-degree* for node i are respectively

shown links emerging from node i to node j, and links originate from node j to i. out-degrees and in-degrees are mathematically defined as follows,

$$\begin{aligned} d_i^{out} &= \sum_{j \in \vartheta(i)} a_{ij} \\ d_j^{in} &= \sum_{i \in \zeta(j)} a_{ij} \end{aligned} \tag{A.7}$$

where $\vartheta(i) = \{j | a_{ij} = 1\}$ and $\zeta(j) = \{j | a_{ij} = 1\}$.

Connectivity: *Connectivity* is another indicator that denotes the number of linkages of a given node. Markose (2012) also defines it as the likelihood of any two nodes being connected in the network.

$$Connect = \frac{\Psi}{N(N-1)} \tag{A.8}$$

where Ψ is the representative of the number of the existing links, which shows the positive net liabilities in the stability matrix Θ, over the total possible direct links, $N(N-1)$.

Clustering Coefficient (CC): *Clustering coefficient* also is a measure that represents the quality of connections between the neighbors of a node in a network. According to Markose et al. (2012), the clustering coefficient assumes that the likelihood of connection for two FIs (i.e., banking system) increases if there is a common counterparty between them. The CC is also defined as a measure of the degree to which nodes tend to cluster together, reflecting how well the neighbors of a node connected together (Holland and Leinhardt, 1971; Watts and Strogatz, 1998). CC can be also expressed in the following mathmatical form,

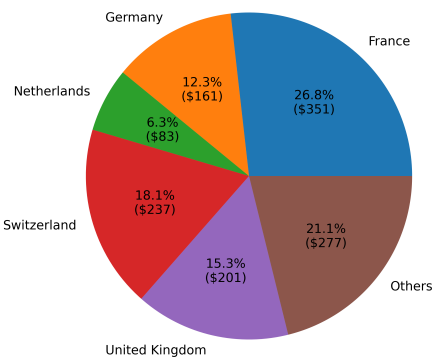
$$CC_i = \frac{L_i}{k_i(k_i - 1)} \tag{A.9}$$

where L_i shows the number of existing links between node i's direct counterparties, and $k_i(k_i - 1)$ denotes the total number of possible direct linkages between counterparties of (bank) country i.

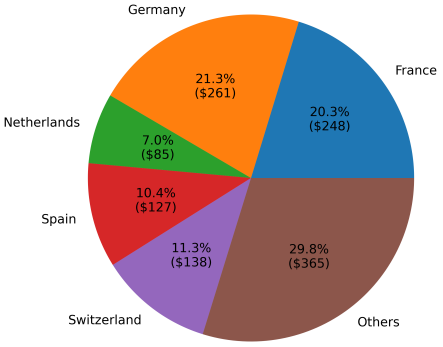
A.6 Annex F - Cross-border banking systems exposures

FIGURE A.6: Cross-border banking systems exposures to the top borrowers

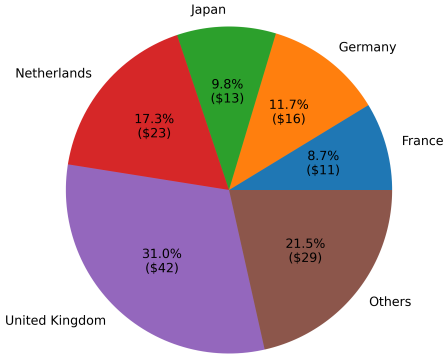
(A) Claims on the United States



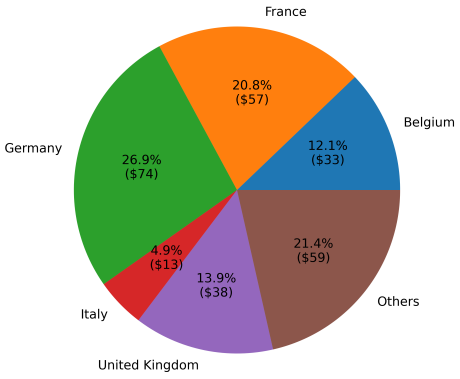
(B) Claims on UK



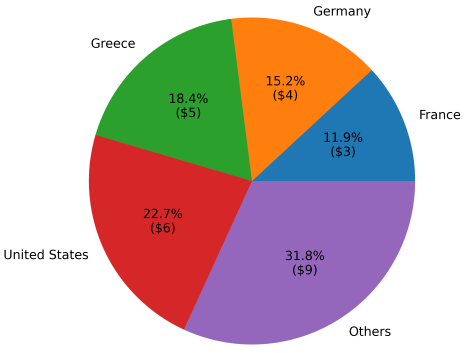
(C) Claims on Australia



(D) Claims on Ireland



(E) Claims on Turkey



Note: Figure plots cross border banking systems exposures to the main 5 borrowers - the US, UK, Australia, Ireland, and Turkey - with their main lenders in 2020:Q1. The figures in the parentheses report the amounts of claims in billion dollars for the associated banking system.

Data source: BIS Consolidated Banking System Statistics.

A.7 Annex G - Node statistics

TABLE A.1: Network statistics

	2006Q1	2006Q2	2006Q3	2006Q4	2007Q1	2007Q2	2007Q3	2007Q4	2008Q1	2008Q2	2008Q3	2008Q4	2009Q1	2009Q2	2009Q3	2009Q4	2010Q1	2010Q2	2010Q3
Node	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
Edges	171	170	171	171	170	169	171	171	171	169	171	171	171	170	171	171	169	170	171
Connect	0.322	0.320	0.318	0.323	0.323	0.318	0.335	0.332	0.333	0.335	0.348	0.342	0.345	0.343	0.343	0.338	0.358	0.352	0.368
CC	0.414	0.411	0.412	0.422	0.422	0.420	0.423	0.423	0.424	0.423	0.427	0.427	0.427	0.421	0.420	0.421	0.426	0.432	0.431
Mean in	7.72	7.68	7.64	7.76	7.76	7.64	8.04	7.96	8	8.04	8.36	8.2	8.28	8.24	8.24	8.12	8.6	8.44	8.84
Std in	8.92	8.75	8.82	8.83	8.89	8.88	8.69	8.75	8.61	8.72	8.53	8.30	8.43	8.37	8.31	8.19	8.40	8.32	8.19
Skew in	0.53	0.47	0.52	0.45	0.50	0.55	0.44	0.51	0.41	0.45	0.38	0.37	0.35	0.35	0.32	0.31	0.15	0.19	0.11
Kurt in	-1.46	-1.54	-1.47	-1.57	-1.45	-1.42	-1.40	-1.35	-1.51	-1.41	-1.36	-1.32	-1.46	-1.43	-1.49	-1.52	-1.73	-1.69	-1.67
Mean out	7.72	7.68	7.64	7.76	7.76	7.64	8.04	7.96	8	8.04	8.36	8.2	8.28	8.24	8.24	8.12	8.6	8.44	8.84
Std out	3.32	3.17	3.24	3.35	3.33	3.16	3.58	3.49	3.45	3.56	3.85	3.67	3.70	3.64	3.52	3.35	3.43	3.44	3.45
Skew out	-0.36	-0.12	-0.21	-0.42	-0.44	-0.50	-0.59	-0.61	-0.29	-0.49	-0.57	-0.49	-0.59	-0.56	-0.33	-0.22	-0.40	-0.32	-0.01
Kurt out	-0.92	-1.08	-0.96	-0.79	-0.69	-0.42	-0.05	-0.16	-0.68	-0.29	-0.22	0.23	0.00	-0.01	0.13	0.34	-0.22	0.38	-0.50
Eigenvalue	0.80	0.93	0.78	0.61	0.92	0.93	0.89	1.12	1.30	1.13	0.51	0.69	0.51	0.47	0.91	0.88	0.80	0.79	0.73

	2010Q4	2011Q1	2011Q2	2011Q3	2011Q4	2012Q1	2012Q2	2012Q3	2012Q4	2013Q1	2013Q2	2013Q3	2013Q4	2014Q1	2014Q2	2014Q3	2014Q4	2015Q1	2015Q2
Node	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
Edges	171	170	170	169	169	169	169	168	169	169	168	168	168	167	167	167	167	167	167
Connect	0.393	0.390	0.388	0.377	0.385	0.382	0.382	0.378	0.387	0.382	0.387	0.387	0.422	0.427	0.420	0.425	0.433	0.435	0.440
CC	0.438	0.440	0.440	0.434	0.435	0.437	0.436	0.434	0.437	0.437	0.438	0.435	0.449	0.449	0.447	0.448	0.455	0.454	0.457
Mean in	9.44	9.36	9.32	9.04	9.24	9.16	9.16	9.08	9.28	9.16	9.28	9.28	10.12	10.24	10.08	10.2	10.4	10.44	10.56
Std in	7.58	7.51	7.42	7.48	7.65	7.40	7.44	7.57	7.60	7.62	7.64	7.64	6.23	6.72	6.76	7.01	6.73	6.61	6.74
Skew in	-0.10	-0.12	-0.14	0.05	0.07	-0.06	-0.06	0.00	-0.04	0.05	0.00	-0.02	-0.50	-0.47	-0.30	-0.28	-0.10	-0.37	-0.30
Kurt in	-1.49	-1.56	-1.51	-1.38	-1.31	-1.43	-1.42	-1.55	-1.50	-1.42	-1.48	-1.50	-0.78	-0.89	-0.75	-1.01	-0.44	-0.82	-0.77
Mean out	9.44	9.36	9.32	9.04	9.24	9.16	9.16	9.08	9.28	9.16	9.28	9.28	10.12	10.24	10.08	10.2	10.4	10.44	10.56
Std out	3.65	3.25	3.15	3.38	3.81	3.34	3.80	3.64	3.63	3.47	3.52	3.54	3.72	3.95	4.11	4.40	4.57	4.44	4.52
Skew out	-0.21	0.20	0.25	-0.12	-0.40	-0.23	-0.13	-0.22	-0.35	-0.38	-0.34	-0.26	-0.01	0.09	-0.10	-0.02	-0.48	-0.41	-0.42
Kurt out	-0.69	-0.52	-0.06	-0.23	-0.18	-0.28	-0.64	-0.70	-0.68	-0.32	-0.53	-0.78	-0.88	-0.58	-0.18	-0.73	0.35	-0.08	0.00
Eigenvalue	0.66	0.87	1.06	0.61	0.76	0.80	0.80	0.79	0.87	0.79	0.69	0.44	0.67	0.82	0.85	0.81	0.59	0.59	0.63

	2015Q3	2015Q4	2016Q1	2016Q2	2016Q3	2016Q4	2017Q1	2017Q2	2017Q3	2017Q4	2018Q1	2018Q2	2018Q3	2018Q4	2019Q1	2019Q2	2019Q3	2019Q4	2020Q1
Node	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
Edges	167	166	167	166	166	167	166	166	165	167	165	167	167	168	165	168	170	165	168
Connect	0.442	0.440	0.438	0.433	0.437	0.432	0.428	0.435	0.435	0.440	0.442	0.435	0.442	0.437	0.440	0.438	0.442	0.437	0.440
CC	0.457	0.455	0.454	0.452	0.455	0.453	0.450	0.455	0.456	0.458	0.459	0.456	0.460	0.456	0.459	0.459	0.460	0.457	0.460
Mean in	10.6	10.56	10.52	10.4	10.48	10.36	10.28	10.44	10.44	10.56	10.6	10.44	10.6	10.48	10.56	10.52	10.6	10.48	10.56
Std in	6.85	6.84	6.60	6.53	6.56	6.56	6.33	6.25	6.39	6.34	6.60	6.51	6.73	6.70	6.80	6.73	6.73	6.62	6.70
Skew in	-0.24	-0.14	-0.34	-0.42	-0.35	-0.33	-0.39	-0.47	-0.39	-0.47	-0.31	-0.45	-0.32	-0.27	-0.28	-0.28	-0.32	-0.29	-0.27
Kurt in	-0.67	-0.50	-0.71	-0.93	-0.66	-0.72	-0.82	-0.59	-0.73	-0.56	-0.67	-0.81	-0.80	-0.95	-0.80	-0.81	-0.80	-0.71	-0.73
Mean out	10.6	10.56	10.52	10.4	10.48	10.36	10.28	10.44	10.44	10.56	10.6	10.44	10.6	10.48	10.56	10.52	10.6	10.48	10.56
Std out	4.71	4.70	4.59	4.44	4.47	4.15	3.98	3.94	4.20	3.98	4.16	4.02	4.24	4.28	4.28	4.23	4.24	4.21	4.35
Skew out	-0.57	-0.54	-0.36	-0.13	-0.24	-0.37	-0.22	-0.15	-0.13	-0.16	-0.11	0.08	-0.10	0.00	-0.16	-0.10	-0.10	-0.16	-0.25
Kurt out	0.17	0.17	-0.09	-0.07	-0.18	0.18	-0.20	0.37	-0.15	0.29	-0.15	-0.48	-0.64	-0.60	-0.36	-0.59	-0.64	-0.16	-0.74
Eigenvalue	0.52	0.39	0.58	0.71	0.71	0.73	0.75	0.72	0.69	0.67	0.76	0.77	0.73	0.62	0.56	0.57	0.58	0.51	0.71

Note: Table reports network statistics for every period from 2005:Q1 to 2020:Q1 for BIS reporting banking systems. The measures in the table stand as follows: Connect stands for connectedness; CC for clustering coefficient; in/out for in/out degrees; Std for standard deviation; Kurt for kurtosis;and Skew for skewness.

Data source: BIS consolidated banking system statistics.

A.8 Annex H - Total global and domino losses.

TABLE A.2: Total global and domino losses for the US, UK, and Spain.

	US		UK		Spain	
Time	Global Losses Equity Capital (%)	Total Domino Losses Equity Capital (%)	Global Losses Equity Capital (%)	Total Domino Losses Equity Capital (%)	Global Losses Equity Capital (%)	Total Domino Losses Equity Capital (%)
2006Q4	1,166(69.60)	147,351 (69.60)	786(23.78)	74,010 (23.78)	237(20.33)	11,144 (20.33)
2007Q4	1,508 (65.16)	126,853 (65.16)	1,374 (28.47)	64,635 (28.47)	775 (30.02)	22,654.34 (30.02)
2008Q4	1,856 (89.45)	209,896 (89.45)	974 (26.35)	101,858 (25.40)	372 (14.15)	112,884 (14.15)
2009Q4	261 (18.06)	317,243 (16.41)	816 (19.95)	0 (19.12)	150 (12.94)	2,945 (12.94)
2010Q4	352 (28.54)	267,112 (25.31)	465 (34.88)	44,348 (34.19)	225 (16.26)	380 (16.26)
2011Q4	451 (31.26)	252,171 (27.82)	388 (29.46)	16,259 (29.46)	104 (15.21)	0 (15.21)
2012Q4	340 (26.15)	241,769 (22.35)	389 (28.49)	0 (27.30)	64 (18.20)	3,897 (18.20)
2013Q4	195 (18.02)	245,663 (16.26)	422 (31.48)	12,626 (31.14)	98 (13.87)	241 (13.87)
2014Q4	353 (20.00)	220,727 (20.00)	364 (24.39)	33,700 (24.39)	78 (11.09)	4,700 (11.09)
2015Q4	198 (15.37)	219,512 (15.37)	376 (22.12)	26,457 (22.12)	39 (9.48)	3,828 (9.48)
2016Q4	159 (15.88)	213,600 (14.19)	296 (22.41)	18,452 (20.55)	33 (11.71)	6,176 (11.71)
2017Q4	219 (20.49)	186,008 (18.90)	292 (13.03)	28,407 (13.03)	13 (12.31)	11,865 (12.31)
2018Q4	230 (25.01)	166,268 (22.90)	367 (11.02)	17,433 (11.02)	10 (11.71)	13,735 (11.71)
2019Q4	225 (17.47)	165,749 (17.04)	226 (10.28)	11,556 (10.28)	9 (9.31)	11,925 (9.31)
2020Q1	285 (21.63)	158,290 (21.63)	261 (18.00)	25,704 (16.66)	9 (9.49)	15,265 (9.49)

Note: Table exhibits total global and domino losses for the US, UK, and Spain for the last quarter of the period 2005 to 2020. Equity capital is reported in billion dollars. Figures which are shown inside of the parenthesis are the percentage of equity capital.
Source: Calculated by author using BIS consolidated banking system data.

A.9 Annex G - Motivations and literature review

This section delves deeper into the motivations and the comprehensive literature review concerning both solvency and liquidity issues.

A.9.1 Solvency Issue

The related literature on solvency issue is mainly covered in two parts. The first part explains the problems around solvency issues in international financial markets, and the second

part discusses the literature behind financial network models that are used to analyze systemic risk from solvency.

A.9.1.1 Solvency Issue in Cross Border Setting

The long-lasting impact of the 2008 financial crisis on the global economy opened a serious debate about the origins of the crisis and spillovers to the integrated international financial system. One of the critical factors that triggered the financial meltdown in GFC were Collateralized Debt Obligations (CDOs) and Mortgage-Backed Securities (MBSs) backed by non-prime loans.[4] The issuance of CDOs, particularly subprime MBSs, grew considerably during 2003-2007, and credit rating agencies failed to estimate the true risk of these securities accurately, and in turn overrated them by marking them falsely as "safe assets" with a high rate of AAA.

The regulated and authorized Financial Institutions (FIs) issued loans, which were secured by claims against mortgagors' purchases, and highly leveraged firms invest heavily in CDOs, in particular those backed by subprime MBSs as collateral. The collapse of collateral prices in late 2007 generated huge loan defaults, causing significant disruptions in both banks and shadow banking systems. Mortgages, which were considered assets for the lenders, became risky due to the potential failure of counterparties' obligations. This generates significant losses for institutional investors and FIs, who intended to invest in high-yielding AAA securities and ultimately contributes to one of the worst global systemic crises in 2008 (Chernenko et al., 2014; Ospina and Uhlig, 2018).[5]

The bursting of a housing bubble in the US real estate market transmitted globally and led to the GFC and has underlined the importance of banking system stability from the cross-border propagation of contagion point of view. The high exposure of European banks to the US

[4] Collateralized Debt Obligations (CDOs), most notably subprime MBSs, are both classes of Assest-Back Securitization (ABS) backed by non-prime loans.

[5] Adelino et al. (2018) compare micro- and macro-prudential analysis around mortgage-backed securities. Further information and details can be found in Barnett-Hart (2009); Ashcraft et al. (2011); Zhang and Xu (2019).

securitized assets led to a 50% equity capital loss (i.e., around $1.6 trillion) underscored the role of cross-border exposures in the dynamic of the 2008 crisis (Allen, 2011) and convinced many that global financial interconnectedness has a critical role in systemic risk and macroeconomic stability (Soramäki et al., 2007; Bruno and Shin, 2013; Castrén and Rancan, 2014). Bailing out of main FIs in the UK, US, and Eurozone countries costs over $14 trillion for taxpayers and reinforced academics and regulators to identify, control, and monitor the failure of FIs that arises from the domino effects of illiquidity and insolvency. The cross-border exposure of banks is considered as one of the main drivers of the 2008 financial crisis in such an integrated international financial system (Degryse et al., 2010; Allen, 2011; Reyes and Minoiu, 2011; Castrén and Rancan, 2014). Similarly, in this research, we aim to track and monitor the risks of exposure that creditors face concerning debts owed to them by other parties, and vice versa, within the interconnected balance sheets of financial institutions (FIs). Our focus is on how these connections among balance sheets create a ripple effect when debtors fail to meet their obligations, impacting others in a connected sequence.[6]

There is one strand of research that mentioned the procyclicality of capital flows within cross-border banks, and how this feature has led to serious financial and economic instabilities. The massive effect of bank capital flows stems from how banks organize their balance sheets. Bank lending is highly procyclical so it grows considerably in booms and drops in crisis (Kaminsky et al., 2004; Brunnermeier and Sannikov, 2014, 2015). They address effective global regulation of cross-border banking systems as a solution for global financial stability and suggest countries to design frameworks to mitigate the risk of cross-border capital flows. The financial structure of global banking systems plays a key role in the transmission of imbalances and global financial stability, thus requiring proper regulatory attention (Brunnermeier et al., 2012).

Additionally, there exists a growing interest in contagious crises and cross-border contagion literature after the EMEs crisis in the 1990s (Claessens and Forbes, 2001). Calvo et al.

[6] Giudici et al. (2020) and Raddant and Kenett (2021) recently highlight the importance of analyzing the structural topology of global banking systems and their vulnerability to the liabilities of debtor sovereigns.

(1993, 1996) differentiate between fundamental-based contagion (spillover) that can occur if the exposed country is linked to a counterparty via finance or trade, and pure contagion occurs if expectations have been changed rather than fundamentals (Eichengreen et al., 1996; Glick and Rose, 1999; Kaminsky et al., 2002). Masson (1999) also explained about Monsoonal effects that will happen if major economic shifts occur in industrial countries that affect EMEs. They explain the role of global push factors and global pull factors in capital flows within countries and underline the importance of push factors in the movement of capital to emerging economies in the late 1990s. Focusing on the banking system, Bruno and Shin (2013) also addresses the global factors related to cross-border capital flow. They highlight solutions focusing on the leverage cycle of global banks and show that the global factors dominate the local ones using the study of 46 countries. Glasserman and Young (2016) review the extensive discussion on the contagion in an interconnected financial system and how it contributes to systemic fragility. They particularly emphasize the interaction between network structure and crucial factors like leverage, size, shared exposures, and short-term funding.

There is another strand of literature that sheds light on interconnectedness within the financial network and exposes the door to systemic risk (Degryse et al., 2010; Cerutti et al., 2012; Castrén and Rancan, 2014).[7] This strand focuses on the interdependency among financial institutions that can magnify disruptions, allowing shocks in one segment to propagate widely, causing losses throughout the system. However, these approaches have failed to introduce a reliable metric for capturing systemic risk. More details regarding systemic risk and financial network models literature are provided in the following subsection.

Finally, there are also studies addressing other factors in aggravating the crisis. For instance, chasing the yield of investors in the form of carry trade behavior exacerbates the GFC and serves as a cross-border banking crisis and results in threats to their liquidity and solvency. Acharya and Steffen (2015) explain sovereign debt crisis during 2007-2013 as a "carry trade" behavior.

[7] Jackson and Pernoud (2021) present an overview of how modern financial networks relate to systemic risk, introducing a taxonomy of systemic risk categories. Their discussion also provides insights on optimal regulation and bailouts regarding banks' portfolios and partnerships.

They show that European banking systems took high risk to return and invested in long-term government bonds with high yield that were financed with short-term wholesale funds at low yield to respond to risk shifting and incentives of regulatory capital arbitrage (Acharya et al., 2013, 2014; Boyson et al., 2014, 2016). Another strand of literature also illustrates the main drivers of international capital flows after financial globalization and explains the heterogeneity of the retrenchment based on time, types, and region of the international capital flows (Milesi-Ferretti and Tille, 2011). See also similar studies addressing the global factors in the movement of capital (Powell et al., 2013; Shin, 2014; Koepke, 2019; Vega Baquero and Santoo, 2022). These papers specifically highlight the crucial role of monetary policy in shifting capital flows between the US, other advanced economies, and various other countries. Since the US and advanced economies followed highly "accommodative monetary policies" following the 2008 crisis, EMEs then received high capital inflows, showing investors' willingness toward higher returns. This raised concerns about the issues that can arise due to the flood of liquidity to emerging markets, blowing up asset prices to risky levels, generating credit booms, and thereby increasing the potential of crisis. Recently, concerns regarding the financial threat have grown even more with the advanced economies' shifts from highly accommodative policies. In the period of integrated capital markets and financial globalization, it is expected that policy actions and financial shocks propagate across borders. Especially after easing monetary policies in response to contractionary shock in advanced economies, spillovers are to be predictable (Habib and Venditti, 2019; Clark et al., 2020; Forbes and Warnock, 2021). Although capital flows and interest rate differentials explained the capital movements, there are also studies that elaborate on other factors of these flows such as differences in expected investment returns, differences in economic growth, and institutional frameworks across countries (Powell et al., 2013)

All these issues have brought up the discussion over the inadequacy of the global financial systems and raised the necessity of policy responses by CB and regulators since the spillover of any disturbance in the global market can lead to financial and macroeconomic instability throughout the whole cross-border banking system (Ghymers, 2017; Icard and Turner, 2019).

Prior to considering possible policies in managing global solvency, cross-border financial networks should be modeled to explain systemically important financial intermediaries and the vulnerability of the countries. The aim of this research is to contribute to the literature by analyzing the network topology of the core global banking system, identifying the most systemically important and vulnerable banking system within the global network, and testing for contagion spillovers.

A.9.1.2 Financial Networks

Modern financial systems are generally characterized and analyzed using network science because of the complexity of financial systems. Most of the network then has been modeled using linkages or connections between both sides of the balance sheets- assets and liabilities- of financial institutions to address accurately issues such as financial risks and instability (Allen and Babus, 2008). This approach makes the financial network a useful tool for analyzing systemic risk and contagion through direct and indirect linkages within countries, financial institutions, and markets. Although there is a lot of theoretical literature on financial networks, some areas are still not fully developed particularly in the role of interconnections, contagion and stability, and real-world mapping of financial flows in systems. Allen and Gale (2000), for instance, study on the relation between banking channels of contagion and liquidity shocks. According to them, banks generally hold deposits in other regions or sectors to supply liquidity if demand is unexpectedly high. If a banking system suffers from a shock in one region, the risk transmits to the other regions through the balance sheets of banks, and this can lead to a severe crisis in adjacent regions in the case of a strong spillover effect.

The first strand of the literature focuses on the relationship between connectivity and resilience of the interbank network. Allen and Gale (2000) show the effect of various network structures in propagating shocks within banks. They discuss that each bank's total exposure is equally divided among its counterparties if the bank's network is complete, and hence risks of failure of each bank and propagation through the system are small. Thus, the whole

system can be more stable and resilient compared to an incomplete financial network, where a failure of one bank can result in the failure of the entire system since each counterparty may be exposed to only one for the total of its receivables. Similarly, Babus (2016) examines the connectivity and contagion within highly interconnected banks and concludes that higher connectivity can enhance resilience and decrease the risk of contagion. Similar results are also gained by Castiglionesi and Navarro (2007), Freixas et al. (2000), Gai and Kapadia (2010).

However, regulators and researchers warn that the default of firms that are too interconnected to other firms that a failure of one can lead to a large propagation of failure in the whole system. This is a phenomenon in the network literature that is known as too-interconnected-to-fail (Gofman, 2017; Markose et al., 2012). Ben Bernanke, Federal Reserve chairman, announced that the too-big-to-fail is an issue that should be solved as well (Bernanke et al., 2010). Elliott et al. (2014) also explains the European debt cross-holdings in terms of "too big to fail" phenomena and the cascades of failures within an interconnected network of financial institutions. They discuss how variation in asset values can lead to the failure of a FI, depending on the structure of the network. Volcker (2012) also point out that "the risk of failure of large interconnected firms must be reduced, whether by reducing their size, curtailing their interconnections, or limiting their activities". Moreover, according to May (2019), connectivity can be a double-edged sword as the impact of connectivity strictly depends on the degree distribution characteristics, taking into account the specific context and structure of the network. Similarly, Battiston et al. (2012) confirm that connectivity and resilience are not a simple monotonic relationship. They examine financial network topology and its effect on the stability in the global crisis and find a threshold that beyond, connectivity can raise instability, and thereby inconsistency increase between agent risk and systemic risk. Although there is no robust consensus on specific structures in networks, all agree on the superiority of merging financial systems and network theory to analyze systemic risk and contagion. Glasserman and Young (2016) review the extensive discussion on the contagion in an interconnected financial system and how it contributes to systemic fragility. They also emphasize the necessity for further exploration into the role of interbank connections

in promoting stability.

There is also a wide range of empirical literature on financial networks even though most of them focused on the interbank market analysis and their channel of contagion. They utilize mainly balance-sheet data to evaluate bilateral credit relations between banking systems, and then default one bank to test the system stability. Angelini et al. (1996, 2008) and Mistrulli (2011) study the Italian interbank market and its potential magnitude of contagion. Furfine (2003) analyzes the US interbank, Wells (2004) assesses the interbank exposures in the UK, and Upper and Worms (2004) applied the network analysis for German banks. The contribution of these studies mainly highlights the role of interconnection and contagion.

Another strand of financial network literature is based on cross-border bank exposure. For instance, Von Peter (2007) studies the topology of global networks using BIS locational bank data. He uses various centrality metrics such as degree, betweenness, closeness, and weighted centrality to show the core-periphery topology in the global banking system and discuss the soundness of international banking centers using financial networks; however, he does not explain the properties of the network for instability in terms of early warning. Minoiu and Reyes (2013) also assess connectivity, clustering, and centrality for the global banking system using BIS locational bank data between 1987 and 2009. Their result shows the global banking network is relatively unstable and reports the structural breaks in the network which is stemming from the swing of capital flows. Moreover, they indicate that connectivity drops during the crisis and after the banking crisis. They also point out the location of the initial shock to the network as another factor that can contribute to the crisis rather than only connectivity. Similar literature can be found in Hattori et al. (2007), Degryse et al. (2010), Allen (2011) and Castrén and Rancan (2014).

There are also studies addressing the pro-cyclical behavior of connectivity in the global banking system using the market price-based systemic risk criteria. Adrian and Brunnermeier (2011), Pedersen et al. (2010), Chan-Lau et al. (2009), Huang et al. (2012), Goodhart and

Segoviano (2009), Tarashev et al. (2010), Gauthier et al. (2012), and Minoiu and Reyes (2013) are some of the research used market price-based to analyze the systemic risk. Degryse et al. (2010) and Borio and Drehmann (2009); Borio and Drehemann (2010) address the paradox of volatility in the performance of the "market-based statistical proxies" and declare that they show the market is very stable and the index is at the lowest and very stable just before the crisis where the financial collapse happens for both credit risk (credit default swap spreads) and market risk (volatility index). And, in the best scenario, the market price measure can simultaneously reveal systemic financial stress. There are cases that they spike after the collapse in the market (Castrén and Kavonius, 2009; Adrian and Brunnermeier, 2011). Minsky (1977) and Borio and Drehmann (2009); Borio and Drehemann (2010) on the contrary criticize these indices for their weak performances. Arsov et al. (2013) also confirmed the disability of 'early' warning of distress using market price-based indices and identified these measures as coincident and near coincident systemic risk measures. Besides, Markose (2012, 2013) questioned these models for the underestimation of risk (volatility) and mentioned the necessity of a systemic risk index that relies on firms' balance sheets and considers direct financial obligations and exposure.[8] Later, Markose et al. (2021) established the eigen-pair method, and the precise development of the spectral R number from epidemiology was adapted and implemented for financial contagion.

Regarding the network models of financial exposures, Hattori et al. (2007) analyzes the topology of the network of cross-border bank exposures using BIS banking data for the period 1985 to 2006. Their finding shows that the network of banking exposure has become more interconnected over time by addressing the higher connectivity between banks, larger average degree, higher clustering coefficient, and shorter average path length. Hattori et al. (2007) also warn on growing systemic risk in the international financial systems. Degryse et al. (2010), aligning with Hattori et al. (2007), investigate cross-border exposures of contagion risk by

[8]There are also non-network studies that discuss the shortcomings of standard systemic risk measures and the lack of early warning. For instance, Bisias et al. (2012) gives an extensive discussion about the lack of consensus on measuring systemic risk, and Iván et al. (2016) questions the availability of information in systemic risk measures.

using BIS consolidated statistics for 17 banks between 1999-2006. They declare a high density of banks and show a growing speed of transmission of contagion. Degryse et al. (2010) also warns about the role of the US banking system that can lead to a destructive contagion effect throughout the international banking system and collapse the entire system. They explain that a shock to 25% to 35% of cross-border liabilities in the US and UK, respectively, can result in domino losses of about 94% and 45% assets in other banking systems. Further, Castrén and Rancan (2014) find similar results on the dynamics of connectivity in the 77 sectors within the Euro area from 1990 to 2012. Castrén and Rancan (2014) analyze the macro-network for the first time and show the links between across non-financial sector and financial sector for each country and within each banking sector. They also suggest that the propagation of contagion depends on the structure of the network that evolves throughout time. Their finding depicts the connectivity growing up to the 2008 crisis and dropping immediately after the crisis.[9]

Furthermore, in the realm of SRIs, Eisenberg and Noe (2001) and Gauthier et al. (2012) are among the studies discussing the significance of power iteration fixed-point algorithms in systemic risk analysis. Eisenberg and Noe (2001) utilize the fixed-point algorithm to distribute exogenous losses among all participants within the financial network. This serves as the initial stage of contagion in their models, ensuring that the losses incurred by one participant maintain internal consistency in line with others. Gauthier et al. (2012) similarly emphasize the pivotal role of fixed-point algorithms in systemic risk analytics, emphasizing their capacity to maintain a high level of internal consistency that aligns with extensive interconnections. Likewise, Markose (2012) used the power iteration fixed-point algorithms and the epidemic literature to suggest an

[9]There is also empirical research that studies financial network and investigate other channels of contagion through payment system in the banking system (See more studies in McAndrews and Roberds (1995); Freixas and Parigi (1998); Freixas et al. (2000) and Furfine (2003)). Allen and Gale (2000) focuses on banking systems with different regions and sectors and shows that the optimal solution for banks is to hold liquidity in case of high demand. Besides, one strand of the research discusses currency crises and their international contagion such as Masson (1999), Eichengreen et al. (1996), and Glick and Rose (1999). Forbes and Rigobon (2002); Pavlova and Rigobon (2008) also provides a theoretical model of contagion that arises from the stock market prices across different countries.

SRI based on the concept of eigenvalue and corresponding eigenvector centralities.[10] Markose et al. (2021) later documented the efficiency of the eigen-pair method SRI compared to other market price-based SRIs. We applied the same method for 19 banking systems for the period 2005 to 2021 and checked for the contagion process in the cross-border banking system.

A.9.2 Liquidity Issue

A.9.2.1 Literature Review

Global Liquidity (GL) is an ambiguous term but generally can be defined as the "ease of financing from international sources". It can also reflect the ability of the global banking system and capital markets to fund financial assets (Caruana, 2014; Eickmeier et al., 2014). GL is then a general concept that captures a broad range of channels including the ability of corporations and FIs to fund investments, the capacity of firms in the process of securitization to access necessary financing to originate loans, to receive loans for packaging into securities, and finally to finance different kinds of guarantees (Cohen et al., 2017; Avdjiev et al., 2020).

Aglietta (2018) also mentioned liquidity as self-fulfilling in the Working Party since assets are liquid, and the majority are interested in holding them. This perception can be altered during the crisis when the characteristics of liquidity can become closely linked. GL can then reflects a measure of the monetary condition in the international economy. It addresses a variable combination of accessibility of funds at a national level and international financial intermediation which links closely national liquidity with foreign sources of funding.

The concept of "ease of financing" is determined and characterized by market participants' attitudes and perceptions towards risk, valuations, and cash flows in the financial and money

[10] Google's PageRank, Katz, and Bonacich centrality are variants of eigenvector centrality (see Brin and Page (1998), Katz (1953), and Bonacich (1987)). The advantage of using the eigenvector metric over others is that the concept of eigenvalue and its associated left and right eigenvector centralities allow us to extract more information about the positions of nodes within a network. Section 2.3 explains more details about the role of right and left eigenvectors in determining important and vulnerable nodes within our cross-border banking system.

market that drive fund and credit extension and liquidity. Any shifts in credit creation and risk-taking approach can have monetary and financial stability consequences, and thereby impact the real economy. Thus, analyzing global liquidity dynamics is required to understand the participants and components of global liquidity (Bruno and Shin, 2015b; Cohen et al., 2017). GL is typically formed by the interaction between the three different components; the asset-liability point of view, the private-official interactions, and the national-international components (Icard and Turner, 2019).

The asset-liability point of view is very useful for measuring the degree of global liquidity. The total amount of credits and the extension of credit can be determined by the asset side or the liability side of the balance sheet of financial institutions. This shows the borrowing volume of firms and allows them to concentrate more on the role of firms' balance sheets in forming overall financing (lending/borrowing) patterns. These components can be very helpful in tracking and analyzing the flow of funds. The BIS balance sheet data that we apply in this study is helpful in highlighting this component of liquidity.

Secondly, the level of liquidity also depends on the interaction of the public sector and private investors, where the key difference is mainly characterized by the source and dynamic of liquidity. Official liquidity is created by the public sector, where for example, CBs and its policy tools generally affect market liquidity by supplying liquidity in the form of Fiat money and reserve balances and by providing the means of payment in the monetary and financial system. However, private liquidity is a key factor in risk exposures in the global financial market as it quantitatively dominates the public sources of liquidity and it is a market-driven component that is formed endogenously by the players of the market (Landau, 2018). Private liquidity is actually the main component that tends to evaporate during financial crises and then liquidity collapses into the official part (Domanski et al., 2011; Ghymers, 2019; Icard and Turner, 2019).

Financial flows and the cross-border banking system are also other components that are

intimately linked to global liquidity dynamics. The cross-border capital flows involve the movement of funds across countries for investment purposes, such as foreign direct investment (FDI), portfolio investment, and bank lending, contributing to the overall liquidity in the global financial system, as capital moves from surplus regions to deficit regions seeking profitable opportunities. Similarly, the cross-border banking system is playing a key role in financial intermediation and facilitating cross-border transactions, acting as a conduit for liquidity transmission across borders. They provide funding, credit, and liquidity services to borrowers and investors across different countries. Subsection **??** provides more details on the global liquidity issues in cross-border components.

The analysis of global liquidity is of utmost importance for several reasons; First, the interaction between the financial cycle (booms and busts) and the real economy deserves more attention than it has received in the past. Global liquidity excesses can contribute to the endogenous build-up of vulnerabilities, and liquidity shortages can have important implications for stability and growth. liquidity shortage can lead to solvency risk. Farmer (2017) and Aglietta (2018) elaborate on how financial markets roll around liquidity and not fundamentals like employment equilibrium. He explained there exist multiple equilibria in the economy, and the beliefs over future liquidity conditions are determinants of which equilibrium. Secondly, the growing impact of global conditions on domestic economies and financial systems. In an interconnected world, global financial cycles have a growing economic impact on domestic economic conditions. Policymakers need to consider these feedback effects. More work is needed to internalize all these interdependencies and spillovers in a consistent framework. We attempt to cover this part through the contagion process in the network.

So far, we have provided a general concept of global liquidity and its components and highlighted the role of liquidity in the international financial market. In the following subsection, we review systemic risk around liquidity in the international financial market and explain the liquidity issues in a cross-border setting.

A.9.2.2 Systemic Risk in Global Market

While global liquidity is essential for economic growth, it also poses several challenges. These challenges and issues can generate important externalities to the system and contribute to systemic risk. It is strictly linked to the International Monetary System (IMS) and seems as a critical factor for the stability of financial systems and fluctuations of the whole world economy. Analyzing the dynamic structure of GL and its evolution clearly points out systemic flaws in the IMS. Since the global financial crisis (GFC), the development of global liquidity reveals the upcoming risk of new episodes of liquidity crunch, warns of the negative spillovers for economies and difficulties for managing GL, which undoubtedly would impose very high costs in the global economy. In this sebsection, we attempt to highlight several challenges to global liquidity: (1) liberalisation and global imbalances; (2) chasing yields and carry trade; (3) Monetary market spillovers (e.g. quantitative easing (QE)).

Liberalisation and global imbalances. One of the main issues arises from the liberalization or integration of financial markets that can create some threats to the international financial system. Although financial globalization and liberalization improved the financial flows and cross-border trade by providing more international risk-sharing possibilities (e.g. diversification of risks) and efficient allocation of capital, it made the financial markets more imbalanced. This affects the direction of net capital flows and its composition of gross flows (Mendoza et al., 2009; Mendoza, 2010; Mendoza and Quadrini, 2010). These global imbalances arise when there are significant differences in trade and capital flows between countries and can affect global liquidity. Countries with persistent current account surpluses contribute to global liquidity by accumulating foreign exchange reserves. On the other hand, countries with current account deficits rely more on capital inflows, which can create vulnerabilities if liquidity conditions suddenly tighten.[11]

[11] Lucas Jr (1990) argue the growth models in describing the behavior of international capital flows. He also warned about the imbalances and financial stability in the global economy when capital is flowing "uphill" or flows from poor countries to rich ones or vice versa. Other studies also attempt to explain the reasons for the flow of capital between through cross-border countries (Gertler and Rogoff, 1990; Eichengreen et al., 2005;

One of the notable features in international economic history is the global imbalances. The gold standard period, the Bretton Woods period, the 1970 petro-dollar crisis, the 1980s twin deficits of the United States, and the 1990s financial flows to emerging markets are all representative of high external imbalances' episodes which had different outcomes - They either unwinding through crisis or sometimes orderly unwinding. They were characterized differently; sometimes flowed uphill, sometimes flowed downhill, sometimes occurred only between industrial economies, and sometimes occurred only across emerging economies.

Chasing yields and carry trade. Financial flows and cross-border trade have been improved by the diversification of risk and efficient allocation of capital. However, globalization raises another phenomenon known as "chasing yield" or the search for higher returns. Financial liberalization allows investment to be more in the form of chasing yields and moving towards the highest return projects. This led to a reduction in the complementary relation between domestic savings and investment, resulting in extreme variation of current account positions across economies. Besides, when interest rates are low or liquidity is abundant, investors may take on greater risk to achieve higher yields. This behavior can lead to the misallocation of capital and the formation of asset bubbles. For example, following the 2008 financial crisis, investors sought higher returns in emerging markets, contributing to rapid credit growth and potential vulnerabilities in these economies.

One instance of yield-chasing investment is a "carry trade" behavior which led to severe losses for banks and resulted in threats to their liquidity and solvency. This strategy involves borrowing funds in a low-interest-rate currency and investing in a higher-interest-rate currency to profit from the interest rate differential. Carry trades can amplify liquidity cycles and lead to excessive risk-taking. When global liquidity is abundant, investors may engage in carry trades, driving up the value of higher-interest-rate currencies. However, when liquidity tightens, carry trades can unwind rapidly, leading to abrupt currency depreciation and market volatility.

Alfaro et al., 2008). Moreover, developing economies, prior to the Asian crisis, mainly issued foreign debt in other dominant currencies like the US dollar, Euro, or the Yen. While they were building up foreign debt, the currency risk for them accumulated more and more and built a borrowing constraint for developing countries.

Acharya and Steffen (2015) explain the sovereign debt crisis during 2007-2013 as a "carry trade" behavior and show that European banking systems took high risk and return and invested in long-term government bonds with high yield that were financed with short-term wholesale funds at low yield to respond to risk shifting and incentives of regulatory capital arbitrage (Acharya et al., 2013, 2014; Boyson et al., 2016). According to Shin (2014), the indicators designed and developed to show vulnerability for the GFC are not useful for the post-GFC because of such behaviour in the global market and new indicators required to monitor instability (see Shin (2014) and Turner (2014) for more details and examples of carry trade).

Monetary market spillovers. After the 2007-2008 crisis, central banks in advanced economies followed highly accommodative monetary policies to improve economic recovery. The issue of a slow recovery forced them to take unprecedented actions to fulfill their mandates such as price stability and maximum employment. In late 2008, the Federal Reserve cut the federal funds rate to the lower bound. They also turned to less conventional monetary policy tools; forward guidance and large-scale asset purchases. Forward guidance decreased long-term interest rates and increased asset prices by reducing private sector expectations about future short-term rates. The second tool, large-scale asset purchases, also put more pressure on the long-term interest rates and asset prices in the same direction as the first tool did, thereby resulting in even more aggressive accommodative financial conditions (Micossi, 2015; Kashyap and Stein, 2023).

A CB enacts quantitative easing by purchasing financial assets such as securities and bonds from commercial banks and other FIs. It thus raises the prices of those assets, decreases their yield, and simultaneously increases the market liquidity (money supply) by growing the excess reserves that banks hold.[12]

[12]The Bank of England was also a pioneer in applying unconventional policy. The BoE adopted a high amount of asset purchases and also used forward guidance for its policy rate. Similarly, the Bank of Japan (BoJ) followed the same policies and engaged in ambitious asset purchases to impede deflation. The European Central Bank (ECB) likewise embarked on providing liquidity by using unlimited long-term refinancing operations. Also, the ECB undertook purchasing securities in distressed markets and declared low interest rates for an extended period. Therefore, CBs in advanced economies implemented unconventional monetary policies to stimulate growth and inflation.

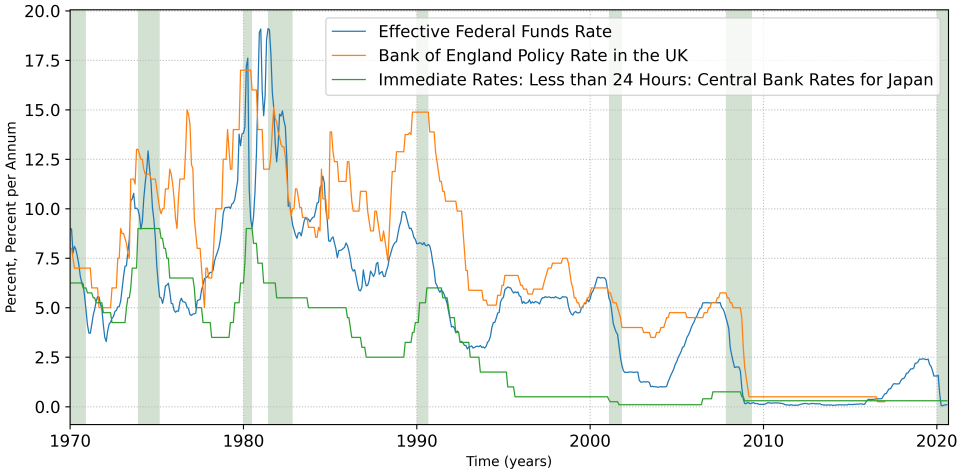
One of the channels through which QE can affect the economy is through portfolio rebalancing. By implementing QE central banks withdraw part of the safe assets from the market into their own balance sheets. It can induce private investors to purchase other financial securities. Thus, investors are forced to "rebalance their portfolio" due to the relative lack of government bonds. It can also decrease those assets' yields as CBs turn to buy other financial instruments that are riskier than government bonds (Powell et al., 2013). Another consequence of QE is the stimulation of bank lending via three channels. First of all, QE increases banks' equity via higher asset prices that can stimulate lending. Secondly, growing the size of CB reserves motivates banks to rebalance their portfolios towards long-term assets such as loans in order to restore the duration risk of holding their assets. QE is also employed to change the relative prices of assets by raising the prices of bonds. Thus, banks have more incentive to rebalance their portfolio to loans rather than bonds (Tischer, 2018).

After the 2007 crisis, quantitative easing (QE), which was supposed to be a semi-permanent remedy, turned out to be an issue and made the interest rate almost zero or negative. The low interest rate led to a "money-go-round" series and asset bubbles which ended up exacerbating financial distress. Similarly, Icard and Turner (2019) discusses the risky size of cumulative balance sheet and QE effects in a decade of low interest rates through aspects of the global economy. In this regard, thanks to the Federal Reserve providing liquidity, banks had gotten used to having huge excess reserves that they could lend out.[13] After the Federal Reserve started unwinding its QE policy back in 2017, lending out the liquidity stopped, and the banks' reserves declined. This issue led them to be more cautious and to hold their resources for themselves. Once the CBs declare unwinding (or, winding) of these policies to conventional (or, unconventional) policy, adverse shocks come out of the blue and restrain the economies (Powell et al., 2013). Sudden changes in monetary policies are not just a one-off event and according to many studies (see Evans-Pritchard (2016); Hannoun and Dittus (2017); Icard and

[13] Kindleberger and Kindleberger (1978) and Kindleberger (1991) warn about the role of asset price bubbles in crises and explains how asset bubbles can arise from the size of liquidity provided in the form of money or credit by the central banks. A known example of this phenomenon is the asset bubbles in real estate and stock prices in Japan in the late 1980s and early 1990s.

Turner (2019)), the risk of an unexpected and unplanned reversal of abundant global liquidity hangs over the world economy, and it is the time to manage the global liquidity.

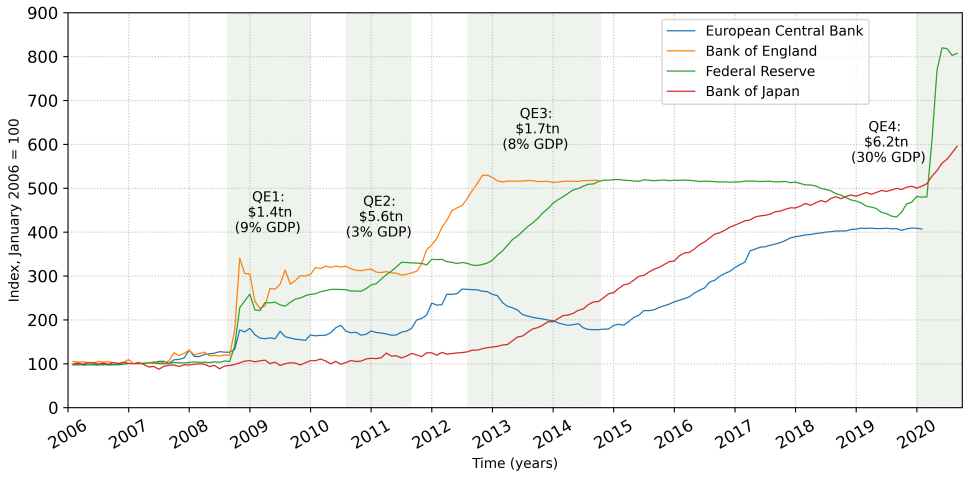
FIGURE A.7: Policy rates for the Federal Reserve, Bank of England, and Bank of Japan.



Note: Most central banks in the developed economies performed "unconventional" monetary policies to maintain price stability and stimulate their economies during the financial crisis mainly by purchasing and selling short-term bonds to reduce short-term interest rates or "policy rates." The graph represents the comovement in these monthly policy rates for the three main banking systems - the Federal Reserve, the Bank of England, and the Bank of Japan - from January 1970 to August 2020: First, they increased their policy rates to control inflation until the period 1981 and then cut those rates after inflation decreased in the 1980s.

Data source: Bank of England, Board of Governors, OECD - FRED.

FIGURE A.8: Total central bank assets



Note: One way of measuring the monetary stimulus of unconventional policy is the value of the assets that central banks hold. The graph shows the total assets of four main central banks - European Central Bank, Bank of England, Federal Reserve, and Bank of Japan - from January 2006 to August 2020 using an index for their values (Normalized to equal 100) in January 2006. The index value allows easy comparison of the relative monetary stimulus rather than the value in each respective currency. QE1, QE2, QE3, and QE4 also highlight periods in which central banks implement quantitative easing policy. Asset holdings for the central banks have all grown highly since the 2008 crisis.

Data source: Bank of England, Bank of Japan, Federal Reserve, European Central Bank - FRED.

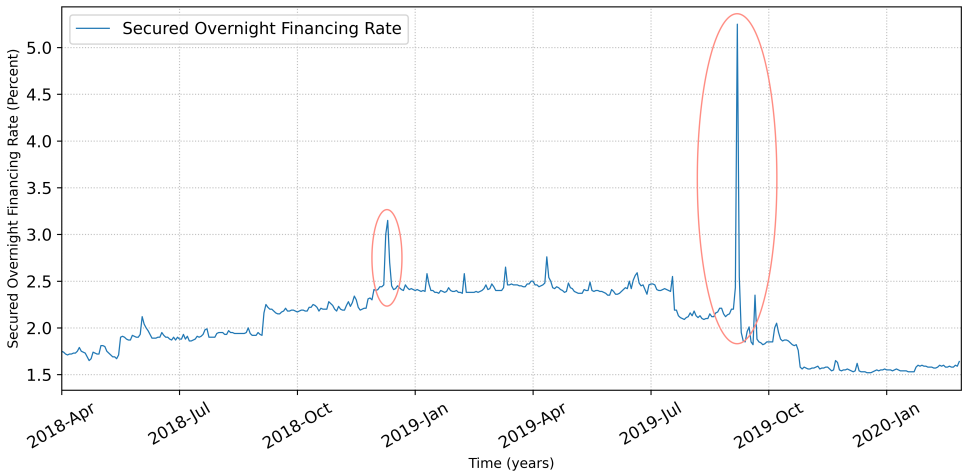
Continuing with the discussion of QE, the interest rate is also fundamentally a monetary phenomenon and is determined by the relative supply of financial assets, preferences of economic players, and risk perceptions. It thus echoes the interaction between the policy rate set by CB, expectation toward future policy rates, and risk premia that prevails in the market and is strictly associated with the markets where borrowing, lending, and financing occur. The repo rate is also an interest rate reflecting the liquidity condition in the money market that can form the borrowing and lending behavior. A repurchase agreement, also known as a repo, is the sale of securities together with an agreement for the seller to buy back the securities at a later date. Gorton (2010) identified the crisis of 2007 to be a "run on the repo" when liquidity in the $14 Trillion repo market dried up. Repo is a type of money that forms of bank debt that grew in significant amounts and was vulnerable to being run on. This market is often referred to as the plumbing of the financial system. Typically, the lender's motivation for taking part in the market is to make a relatively risk-free short-term return on their money as their positions are collateralized by high-quality liquid assets. Thus, if the borrower cannot repurchase the

securities as agreed, the lender can sell them in the market to recover the debt. In the run-up to the GFC, the collateral was primarily Asset Back Commercial Paper (ABCP) conduits based on Residential Mortgage-backed Securities (RMBS) which included subprime mortgages. With the collapse of the US house prices, the ABCP-backed repo markets suffered a run on the repo. This led to a liquidity or credit crunch once the liquidity supplier withdrew from the repo markets and the repo rates spiked by 80%. This spike resulted in the drop in GDP and the 2007 recession in the UK, Europe, and the US (Hördahl and King, 2008). In a similar way, the repo market that bubbled over in September 2019 which reflects the issues with the repo rate still exist.

Icard and Turner (2019) also alert about global liquidity and its challenges and urge the Federal Reserve to take some action to control it. One of the issues is that Repo rates are typically low in normal times since the deals are collateralized and seen as being quite safe, and the market is not usually very volatile. This changed significantly in Sep 2019 once the overnight repo rate shot up from around 2% to more than 5% within a week (see Figure A.9). Since the repo market is so sensitive to the financial world, any disruptions can lead to ripples through the whole system. It seems due to a liquidity crunch, the supply of cash available to lend out has reduced at the same time that demand for cash increased as more securities flooded into the market with an increase in demand and a decrease in supply the rate shot up.[14]

[14]Moreover, Fuhrer (2018) and Kotidis and Van Horen (2018) explain some of the issues that can happen. Firstly, Fuhrer (2018) report the risk of liquidity stemming from corporate tax payments and the role of the repo market in financing large settlements of Treasury debt auctions at the same time. Kotidis and Van Horen (2018) also illustrate that the most repo market activity moves between four large banks; JP Morgan, Bank of America, Citigroup, and Wells Fargo. Also, basically, if these banks reduce even slightly their lending, the market will suffer massively.

FIGURE A.9: Secured overnight financing rate



Note: The graph shows the daily Secured Overnight Financing Rate (SOFR) from April 2018 to October 2020. Shading indicates the covid-19 ongoing recession period.
Data source: Federal Reserve Bank of New York - FRED.

After all, since a failure to monitor and control liquidity risk led a number of financial firms into difficulty, policymakers, and the Basel Committee introduced some global liquidity standards for the purpose of creating a more resilient global banking system, particularly when addressing issues of liquidity.[15] However, poor design of Basel regulations can also increase the risk of solvency in the financial market, and a critical issue in the construction of these regulations is itself part of the problem (Allen et al., 2017). The objectives of these reforms were to improve the regulation, supervision, and risk management in the global system.

In this regard, the Liquidity Coverage Ratio (LCR)[16] is designed to guarantee that banks hold sufficient stock of high-quality liquid assets (HQLA)[17]. Likewise, Basel III addressed

[15]Basel III post-crisis reforms, which was an internationally agreed set of measures, are the last regulations that were introduced to increase the overall (resilience of) financial system stability in response to the crisis.

[16]The LCR is the ratio of the bank's stock of unencumbered HQLA to its projected net cash outflows during 30 days. LCR is generally designed to measure the ability of an institution to withstand a stressed funding scenario (a severe liquidity freeze) and a Net Stable Funding Ratio (NSFR) aims to address liquidity mismatches (Roberts et al., 2018).

[17]HQLA is defined as assets or cash that can be quickly altered into cash without loss of value through sales or being pledged as collateral. This allows FIs to survive a significant liquidity issue over a 30-day stress period.

structural resilience through another liquidity ratio, the Net Stable Funding Ratio (NSFR).[18] While the LCR measure is expected to restrict mismatch issues, and thereby lower the systemic risk, the result of LCR on the creation of liquidity is still ambiguous and should be examined more (Allen et al., 2017; Brunnermeier and Krishnamurthy, 2014; Adrian and Boyarchenko, 2018). Since the creation of liquidity is reduced as a result of increasing the reserves of HQLA on bank balance sheets, banks may increase the share of illiquid assets in their non-HQLA portfolios to offset the effect. Thus, systemic risk arising from restricting liquidity can increase. Likewise, as LCR results have a similar correlated exposure, the systemic risk grows (Cecchetti and Kashyap, 2018).

A lack of a proper conceptual framework impedes the analysis of global liquidity issues, improvement, and implementation of powerful policy responses. Domanski et al. (2011) warns earlier about the lack of measurements and sufficient frameworks to discuss global liquidity conditions and explains how the collapse of interbank markets in the Euro crisis led to calls for the development of safety nets, but it did not suggest adequate measures to signal the increase of vulnerabilities. Domanski et al. (2011) emphasizes the monetary policy as a driver of global liquidity in the economy. Icard and Turner (2019) also recently mentioned the lack of an adequate framework and warned that "central banks and policymakers failed to diagnose the loss of international confidence in the sustainability of many large banks, and how it led to serious global recession." The Working Party also calls for a sufficient framework to monitor and control liquidity before the crisis strikes.

In conclusion, global liquidity, shaped by financial flows and the cross-border banking system, is crucial for the functioning of the global economy. It enables the availability and ease of access to funds and credit, facilitating economic growth and investment. However, managing global liquidity poses challenges, including the risk of misallocation of capital, the impact of

[18]NSFR is calculated by dividing the available amount of stable funding by the required amount of stable funding at least for one year; deposits, long-term wholesale funding, and equity are considered as stable funding. The required amount of stable funding is also estimated by weighting assets. The NSFR aims to show risks that can happen from significant maturity mismatches between liabilities and assets.

carry trades, and the potential vulnerabilities arising from global imbalances. Policymakers and market participants call for the appropriate methodology to monitor, evaluate, and regulate systemic risk carefully and navigate the above challenges to maintain stable and sustainable global liquidity that supports economic growth.

A.9.2.3 Liquidity Issue in Cross Border Setting

In the previous part, we explained the general issues and systemic risks in global liquidity. This part shifts towards highlighting the intricate challenges surrounding liquidity in a cross-border setting.[19] Within the realm of cross-border financial flows and the banking system, a vital role emerges in facilitating international transactions and liquidity transmission across nations. This interconnectedness of the cross-border banking system supports the efficient allocation and distribution of liquidity globally, thereby stimulating economic activity and investment (Ghymers, 2017).

A historical backdrop of global imbalances is significant, encompassing periods such as the gold standard era, Bretton Woods agreement, the 1970 petro-dollar crisis, the 1980s twin deficits of the United States, and the 1990s surge of financial flows to emerging markets. These imbalances varied in nature, direction, and participant type. The work of Lucas (1990) underscores the behavior of international capital flows, particularly the potential instability when capital flows disproportionately from poorer to wealthier countries, or vice versa. The reasons behind such capital flows have been analyzed by various studies. Developing economies, especially before the Asian crisis, heavily leaned towards foreign debt issuance in dominant currencies, creating currency risks and borrowing constraints (De Galhau et al., 2019). Current observations highlight the historical peak of global imbalances, presenting potential threats to the world economy (see Gertler and Rogoff (1990); Eichengreen et al. (2005); Alfaro et al. (2008); De Galhau et al. (2019) for more details on global imbalances).

[19] The extensive literature on solvency and liquidity issue in cross-border setting explained in Chapter 2, Section 2.2

Milesi-Ferretti and Tille (2011) delve into the drivers of international capital flows, highlighting the heterogeneity in the timing, types, and regional aspects of these flows. The resilience of emerging economies in the face of global retrenchment is emphasized. Powell et al. (2013) emphasizes the challenges posed by large and volatile cross-border capital flows to emerging economies, underscoring their potential impact on growth, stability, and vulnerabilities. The role of advanced economies and global factors, particularly monetary policy, in driving capital flows and asset prices has been a growing concern (Shin, 2014). The literature explores the intricacies of capital flows, considering factors beyond interest rate differentials, such as expected investment returns, economic growth, and institutional frameworks. Additionally, the pro-cyclical nature of capital flows and the risks they pose, along with cross-border contagion and spillovers, are examined extensively. The role of interconnected banking systems and their regulation in ensuring global financial stability is emphasized, with a call for effective global and targeted regulatory frameworks (Brunnermeier et al., 2012).

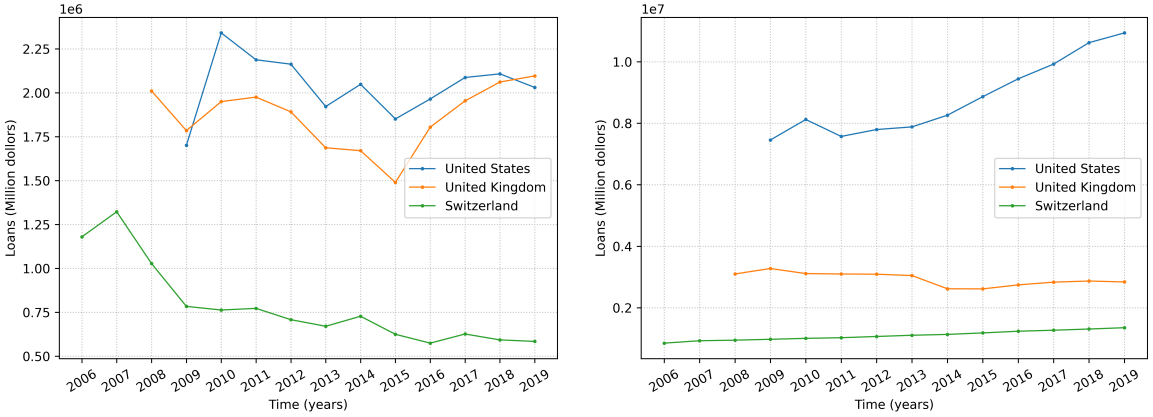
The expansion of financial flows and cross-border trade was further accelerated by the liberalization of capital controls, aiming to enhance international risk-sharing possibilities and capital allocation efficiency. This evolution led to a reduced correlation between domestic savings and investment, resulting in volatile current account positions globally. Instances like the "carry trade behavior" underscore the pursuit of high yields, which can escalate risk, causing liquidity and solvency threats. Emerging market corporations have also increased international debt issuance, leading to currency mismatches and susceptibility to carry trade dynamics (Shin, 2014; Turner, 2014) (studies such as (Acharya et al., 2013; Boyson et al., 2014; Acharya and Steffen, 2015) explains more details on the carry trade behavior). Moreover, the impact of monetary policy actions and financial shocks propagating across borders is a crucial consideration. The interplay of interest rates, investor behavior, and portfolio rebalancing amplifies capital flows to emerging markets during accommodative monetary policy phases. However, the reversal of such policies can lead to reduced capital flows and upward pressure on currencies and asset prices (Powell et al., 2013).

Cross-border contagion and spillovers have drawn attention after the financial crisis propagated from one country to another one (Claessens and Forbes, 2001). The cross-border exposure of banks is considered one of the main drivers of the Global Financial Crisis (GFC) in the presence of an integrated international financial system (Haldane, 2009; Allen, 2011; Minoiu and Reyes, 2013; Castrén and Rancan, 2014). The bursting of a housing bubble in the US in the Global Financial Crisis (GFC) that transmitted globally has again underlined the importance of banking system stability from the cross-border propagation of contagion point of view. The high exposure of European banks to the US securitized assets led to a 50% equity capital loss (around $1.6 trillion) underscored the role of cross-border exposures in the dynamic of 2007 crisis (Allen, 2011), and convinced many that global financial interconnectedness has a critical role in systemic risk and macroeconomic stability (Soramäki et al., 2007; Degryse et al., 2010; Castrén and Rancan, 2014). The financial structure of global banking systems plays a key role in the transmission of imbalances and global financial stability, thus requiring proper regulatory attention (see Allen and Gale (2000), Degryse et al. (2010), and Bruno and Shin (2013) for the banking channels of contagion). Macro-prudential policies then can play a critical role in this part by imposing targeted regulation on systemically important banking systems and monitoring the vulnerable sovereign in cross-border banking systems (Brunnermeier et al., 2012).

The ongoing discourse calls for comprehensive policy responses to address the challenges posed by global liquidity spillovers. The study seeks to contribute by modeling global liquidity within a cross-border banking system, analyzing network topology, and assessing vulnerability and contagion effects. Through these efforts, the aim is to shed light on the instability of the cross-border financial system and formulate strategies for enhanced stability in the face of potential liquidity shocks (Castrén and Rancan, 2014).

FIGURE A.10: Geographic Distribution of Total (in million dollars)

(A) Loans to Developed Economies (B) Loans to Emerging Economies



Note: The Figure shows the geographic distribution of total loans (in million dollars) yearly for the three core economies - United States, United Kingdom, and Switzerland - from 2006 to 2019. The data is cross-border consolidation basis.

Data source: IMF

Appendix B

Complementary Materials for Liquidity Origins of Aggregate Fluctuations

B.1 Network Centralities

This part mainly explains the network centralities, Katz centrality and edge betweenness centrality, used to construct the network index in Section 4.3.1. We also provide the details of the network index including the effect of each centrality on the network index. This is what we referred to as pure node effect and pure linkage effect.

Katz centrality: We use *Katz centrality* as a node centrality to capture the relative influences of a node within the netwok. Katz is basically a measure of the "influence" of a node in the adjacency matrix A (here, associated with the directed network X in Section 4.3.1) that takes into account both direct and indirect linkages.[1] It computes the relative influence of a node within a network by measuring not only the number of the immediate neighbors (first degree nodes) but also all other nodes connected to the immediate neighbors. Connections made with distant neighbors are, however, penalized by an attenuation factor α. Katz centrality is mathematically defined as:

[1]Katz centrality is a variant of eigenvector centrality. The advantage of Katz centrality compared to eigenvector centrality is that the former considers the indirect connections as well.

$$c_K(i) = \sum_{k=1}^{\infty} \sum_{j=1}^{n} \alpha^k (A^k)_{ji} \tag{B.1}$$

where the element at location (i, j) of A^k (i.e., X^k) reflects the total number of paths of k degree connections between nodes i and j. $(A^{[k]})_{ij}$ indicates the presence or absence of a financial transaction or connection between nodes. More specifically, if there is a financial transaction or interaction between node i and node j, then the entry A_{ij} is positive liability amount. On the other hand, if there is no direct financial interaction between nodes (i.e., sectors), then A_{ij} would be zero. The attenuation factor α controls the influence of indirect connections and penalizes the further apart than the immediate node. A typical choice for α is between 0 and 1, where factors closer to 1 give more weight to distant connections, while values closer to 0 emphasize more on local connections (Katz, 1953). This study gives more weight to the local financial interation and choose the default moderate value of $\alpha = 0.1$.

We used the Average Katz Centrality (AKC) to address the global Katz centrality due to the identification problem explained in Section 4.3.2. The AKC is simply the mean of Katz centralities over all nodes in the network, given by:

$$\overline{c_K(i)} = \frac{1}{n} \sum_{i=1}^{n} c_K(i) \tag{B.2}$$

where $\overline{c_K(i)}$ is the AKC, and n is the number of nodes (i.e., sectors). In a financial network context, Katz centrality can help identify institutions that are important in the flow of debt and financial relationships, even if they do not have high degree or direct connections to other institutions. The AKC can provide a summary measure of the overall influence of institutions in the network.

Edge Betweenness Centrality (EBC): EBC measures the importance of edges in the directed network X based on the number of shortest paths between pairs of nodes that pass

through those edges. The EBC is often used to identify the ranking of edges based on their contributions as "bridges" (i.e., important connectors) between different parts of a network.

$$c_B(i) = \sum_{s,t \in V} \frac{\sigma(s,t|i)}{\sigma(s,t)} \tag{B.3}$$

This shows the formula that calculates the betweenness centrality of a specific edge i by summing up the fraction of all-pairs shortest paths that pass through i, where $\sigma(s,t|i)$ denotes the number of paths passing through edge i, and $\sigma(s,t)$ is the number of shortest (s,t)-paths. In this study, edge betweenness centrality can help to identify debt relationships that are important in connecting different group or clusters of sectors in the network (Freeman, 1977; Freeman et al., 2002).

The average edge betweenness centrality (AEBC) that is used to calculates the global edge network effect is simply the mean of edge betweenness centrality over all edges in the network, given by:

$$\overline{c_B(i)} = \frac{1}{n} \sum_i c_B(i) \tag{B.4}$$

where $\overline{c_B(i)}$ is the AEBC, and n is the number of nodes (i.e., sectors). In a financial network context, edge betweenness centrality can help identify debt relationships that are important in connecting different groups or clusters of institutions in the network. The AEBC can provide a summary measure of the overall importance of debt relationships in the network.

Once we define the centrality measures we use in Equation 4.5 to indentify the network effect of the sectors in the US economy, Table B.1 exhibits the regression results for Equation 4.5.

TABLE B.1: Network effect

	Dependent variable:
	Network effect
$\overline{c_K(i)}$	0.837^{***}
	(0.049)
$\overline{c_B(i)}$	0.257^{***}
	(0.017)
Constant	-0.193^{***}
	(0.017)
Observations	60
R^2	0.863
Adjusted R^2	0.858
Residual Std. Error	0.003 (df = 57)
F Statistic	179.581^{***} (df = 2; 57)
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: Table reports the regression applied to construct the network index, which is fitted value of $c_T(i)$, $\widehat{c_T(i)}$, explained in Section 4.3.1. $\overline{c_K(i)}$ denotes the average Katz centrality and $\overline{c_B(i)}$ is the average edge betweenness centrality.

According to Table B.1, the Equation 4.5 can be written in the following form,

$$c_T(i) = -0.193 + 0.837\ \overline{c_K(i)} + 0.257\ \overline{c_B(i)} \tag{B.5}$$

B.2 The Hodrick and Prescott (HP) Filter

The HP filter for the first time introduced by Hodrick and Prescott (1997) as a popular tool in macroeconomics to decpmpose a time series from raw data, especially in business cycle

theory.[2] The reasoning filter decomposes a time series y_t into two components; a trend or growth component g_t and a cyclical component c_t.

$$y_t = g_t + c_t \tag{B.6}$$

The decomposition solves for the growth component to minimize the sum of the squared deviations of the actual series y_t from the growth component g_t, and subtract it from the product of penalty λ and the sum of the squares of the trend component's second differences.

$$\min_{g} \sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=2}^{T-1} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2. \tag{B.7}$$

The second term attempts to penalize changes in the rate of growth. λ captures the magnitude of the penalty for the variations in growth rate of the trend component. In this paper, the λ is 1600 as Hodrick and Prescott (1997) suggests for the quarterly data.

[2] Hamilton (2018) critisizes the choice of λ and the ability of the HP filter to derive cycles when none exist and proposes his own approach to decompose the data. However, Hodrick (2020) later simulates both filters and shows that both approaches Hamilton (2018) and Hodrick and Prescott (1997) work properly although the efficiency of them varies under different conditions and based on the complexity of the model. This paper uses the first difference approach and Baxter and King (1999) filter to avoid any mistake. Under the sensivity analysis, the results is very similar. However, we chooses HP filter over Hamilton (2018) and Baxter and King (1999) as the former is less restrictive compared to the other two methods that drop some observation during the filtering. HP filter has also advantage of smoothing the noise compared to the first difference.

B.2.1 Summary Statistics Table

TABLE B.2: Applied Variables and Summary of their Statistics

Type of Variables	Variables	Min	1st Qua.	Median	Mean	3rd Qua.	Max	Source
Endogenous Variables	log(GDP)	16.14	16.27	16.40	16.39	16.49	16.61	Calculated from FRED
	Repo rate	0.07	0.12	0.20	1.21	1.85	5.26	FRED
	Quick ratio	1.098	1.193	1.225	1.217	1.254	1.331	Datastream
	Mean degree	37.20	73.72	77.60	78.94	84.52	112.61	Calculated from Datastream
	Variance degree	1689	8491	10411	11886	16327	23015	Calculated from Datastream
	Network index	0.061	0.083	0.086	0.084	0.088	0.091	Calculated from Datastream
Exogenous Variables	Log of Monetary base	13.60	14.47	14.97	14.70	15.16	15.44	FRED
	Federal funds rate	0.06	0.12	0.19	1.23	1.92	5.26	Datastream
	Consumer price index	-2.30	0.30	0.50	0.46	0.80	1.50	FRED
	Dollar exchange rate	86.81	92.55	98.08	101.43	111.62	121.84	FRED

Note: Table reports the variables applied in the study and summary of their statistics for the sample period of 2006Q1 to 2020Q4.

B.3 Model Specification

B.3.1 The AR model selection criteria

TABLE B.3: The AR model selection criteria

(A) The selection criteria scores for the AR orders

Selection criterion	AR orders				
	1	2	3	4	5
AIC(n)	-2.549	-2.510	-2.483	-2.593*	-2.574
HQ(n)	-2.514*	-2.452	-2.403	-2.489	-2.448
SC(n)	-2.459*	-2.360	-2.273	-2.323	-2.244
FPE(n)	$8.5e^{-7}$	$1.2e^{-6}$	$1.7e^{-6}$	$6.1e^{-7*}$	$8.2e^{-7}$

(B) The best AR lag length order suggested by each criterion

Selection criterion	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
AR order	4	1	1	4

Note: Table reports the selection criteria and their corresponding scores for the AR orders of 1 to 5.

B.3.2 Augmented Dickey Fuller (ADF) unit root tests

TABLE B.4: ADF unit root tests for the time series variables of interest

Variable	No. of lagged differences	Test statistic	Critical value
GDP	0	-4.352	0.01
	3	-1.9199	0.60
$\mathcal{C}$**(GDP)**	0	-11.707	0.01
	3	-4.6217	0.01
Repo rate	0	-5.295	0.01
	3	-2.2844	0.45
$\mathcal{C}$**(Repo rate)**	0	-10.167	0.01
	3	-4.8361	0.01
Quick ratio	0	-0.9973	0.93
	3	-1.176	0.90
$\mathcal{C}$**(Quick ratio)**	0	-7.3861	0.01
	3	-3.1472	0.11
Network index (NI)	0	-2.8454	0.23
	3	-3.3945	0.06
$\mathcal{C}$**(NI)**	0	-7.3683	0.01
	3	-5.6684	0.01
Mean degree	0	-2.3424	0.34
	3	-3.3945	0.06
$\mathcal{C}$**(Mean degree)**	0	-6.2683	0.02
	3	-5.6684	0.01
Variance degree	0	-3.0051	0.43
	3	-2.3745	0.07
$\mathcal{C}$**(Variance degree)**	0	-7.7943	0.02
	3	-4.7354	0.01

Note: Table reports Augmented Dickey Fuller (ADF) unit root tests for the variables of interest for the sample period of $2006Q1$ to $2020Q4$. $\mathcal{C}(\cdot)$ denotes the time series cycle calculated by the HP filter explained in Appendix B.2.

B.4 Model Diagnostics

Model diagnosis is also performed to evaluate the goodness of fit and the validity of required assumptions in the SVAR model. We use the following procedures to assess whether the model output adequately represents the data and whether any issue in data can be problematic.

B.4.1 Stability Test for VAR model

For the time series variables y_t in equation (4.7), the stability of the VAR representation can be determined by calculating the roots of the following equation:

$$(I_n - A_1 L^1 - A_2 L^2 - ...)y_t = A(L)y_t \tag{B.8}$$

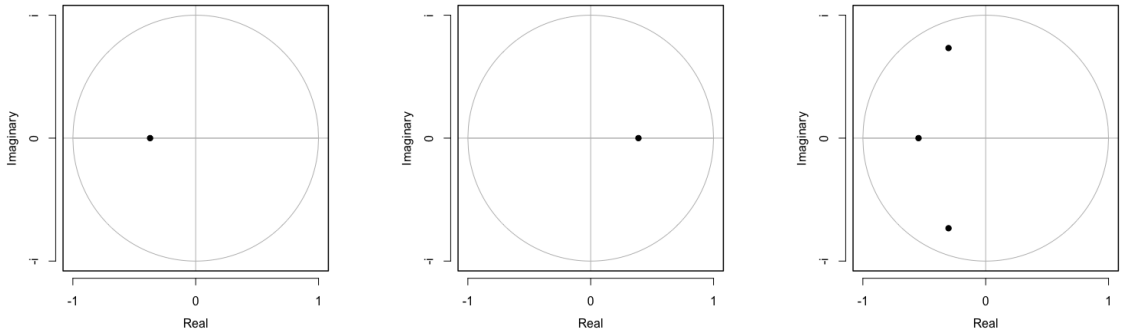
if we define the characteristic polynomial as:

$$\Phi(z) = (I_n - A_1 L^1 - A_2 L^2 - ...) \tag{B.9}$$

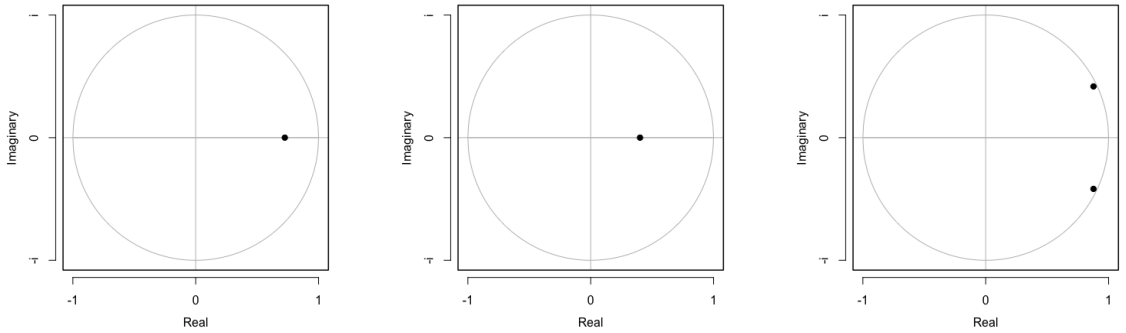
Then the necessary and sufficient condition for stability of model is that all characteristic roots of $\Phi(z)$ lie within the unit circle. Figure (B.1) shows the stability unit circle with inverse roots of AR characteristic polynomial. It confirms the stability condition of VAR system as the inverse toots are all inside of the circle, i.e. the roots are less than one, and thereby the system is stable.

FIGURE B.1: Stability Test for VAR model

(A) Mean degree (B) Variance Degree (C) Network Index



(D) Liquidity Ratio (E) Real GDP (F) Repo Rate



Note: Figure represents the stability unit circle with the inverse roots of AR characteristic polynomial.

Data source: Plotted by author using the databases explained in the data table.

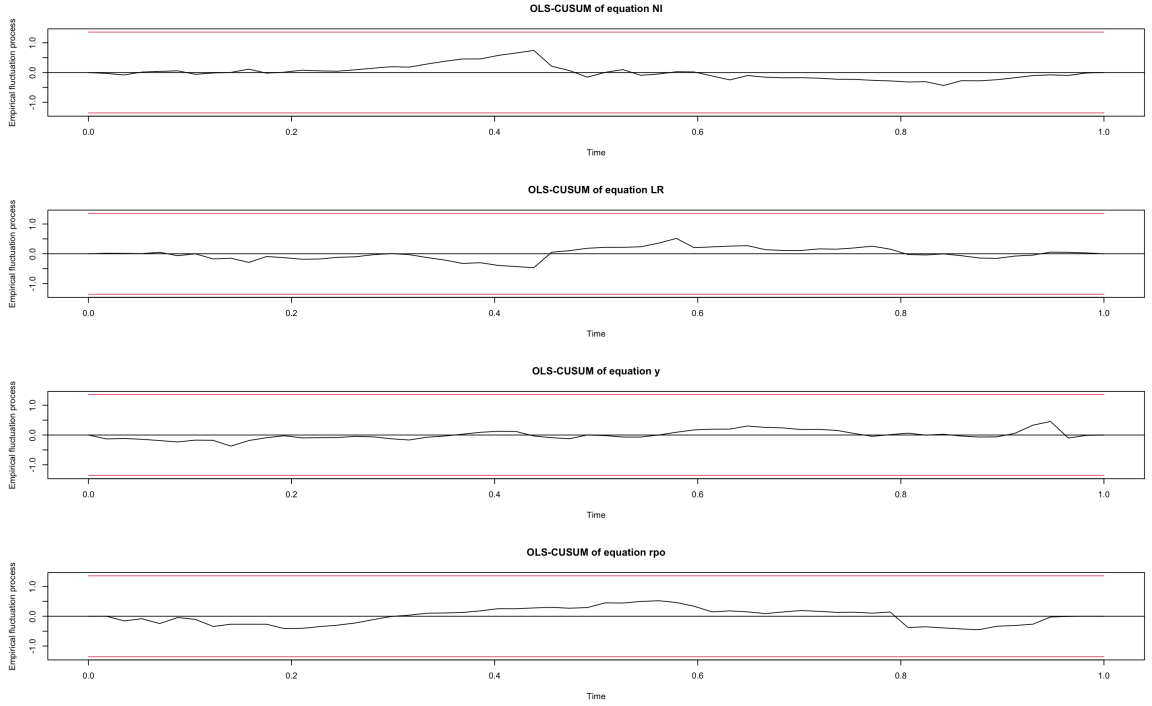
B.4.2 Structural Break

In this subsection we test for the stability of the system to examine whether the model remains stable over time periods or any structural breaks can be detected in the relationships between key variables of interest. This is required to ensure that the estimated relationships or parameters of the SVAR model hold over time. This can provide insights into the overall health of an economy and identify structural changes that may have occurred.

We use the OLS CUSUM (Ordinary Least Square Cumulative Sum Test) test to detect structural changes or instability in a model over time. The test statistic (CUSUM statistic) is calculated for the OLS regression model at different proportions of data, ranging from 0%

to 100%. The proportion of data used for the test increases gradually as we move across the x-axis from 0% to 100%, and the CUSUM statistic is computed at each proportion and shown in the y-axis. The Figure B.2 shows the model stable as CUSUM statistic fluctuates around zero and does not crosses or exceeds the critical values (confidence interval) as the proportion of data increases, showing no significant structural breaks or instability.

FIGURE B.2: Stability Test for Structural Breaks



Note: Figure represents stability testing to assess the stability of relationships between the variables of interest over different time periods. The y-axis plots the CUSUM test statistics, and the x-axis is the proportion of data used for the test. As the CUSUM statistic line does not break the confidence interval (the red line), we can conclude that the model is stable over the time.

B.4.3 Residual Analysis

Residual analysis is an important step in the evaluation of a SVAR model and involves examining the residuals obtained from the estimation of SVAR. This is to assess the properties of estimation and ensures the model representative meet the assumptions.

Autocorrelation analysis: The autocorrelation test, also known as the serial correlation test, is tested to check if there is any presence of correlation between the residual of different lags. Serial correlation occurs when the residuals are correlated with the residuals within the data over the time, which violates one of the assumptions of the VAR model. The residuals of the model are the differences between the observed values and the predicted values, and ideally there should be no systematic patterns or correlations available in them. I used the Ljung-Box test and Portmanteau test to detect whether there are any significant correlations in the residuls at different lag orders.

The Ljung-Box test in Table B.6 is used to assess the presence of autocorrelation in the residuals of a model. The test statistic of the model follows a chi-squared distribution under the null hypothesis of no autocorrelation. The high p-values ($p > 0.05$) in the test suggests that there is no strong evidence to reject the null hypothesis of no autocorrelation in the residuals. Hence, we can conclude that there is no significant autocorrelation present in the residuals for the lag order tested (in this case, up to lag 10) for the variables of interest in the SVAR model.

TABLE B.5: Results of the Box-Ljung Test

Variable	**test statistic Q**	**df**	**p-value**
Repo rate	4.45	10	0.92
GDP	6.50	10	0.77
Quick ratio	9.12	10	0.52
Network effect	9.92	10	0.45
Mean degree dist.	5.33	10	0.86
Variance degree dist.	8.11	10	0.61

Note: Table reports the results of the Box-Ljung test. The null hypothesis in the Box-Ljung test is that there is no autocorrelation in the dataset. The test statistic Q is calculated based on the sample autocorrelation function (ACF) values. The p-value is compared to a significance level ($\simeq 0.05$) to make decision.

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

The Portmanteau Test is also performed as it is specifically designed to check for serial correlation in the residuals of a time series model. With a p-value of 0.61, the test suggests that there is insufficient evidence to reject the null hypothesis, indicating that we fail to reject the null hypothesis and thereby the model's residuals show no significant autocorrelation. This

implies that the residuals of the VAR model are independently distributed and no significant autocorrelation detected in the model's residuals.

TABLE B.6: Results of the Portmanteau Test (asymptotic)

Variables	**Chi-squared**	**df**	**p-value**
B model	137.11	144	0.61
AB model	136.11	128	0.27
Mean degree	147.32	128	0.11
Variance degree	139.93	128	0.22

Note: Table reports the results of the Portmanteau Test (asymptotic). Test Statistic (Chi-squared) measures the discrepancy between the observed autocorrelation of the residuals. The degrees of freedom (df) in the test is determined by the number of lags used in the autocorrelation calculation. The p-value is the probability of observing the test statistic under the assumption that the null hypothesis of no autocorrelation in the residuals.
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

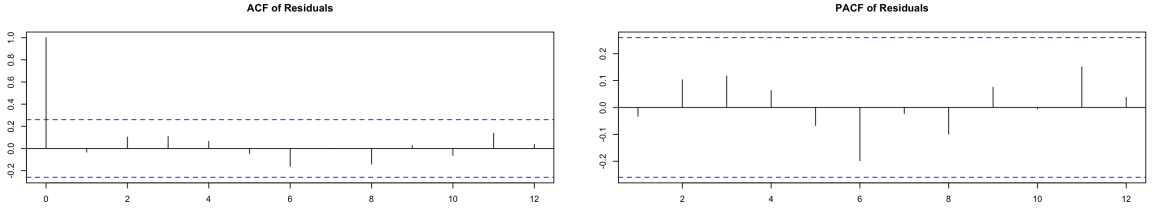
In summary, the Box-Ljung and Portmanteau Test suggests that the VAR model provides a good fit to the data because of no evidence of significant autocorrelation in the residuals. Even though we tested the autocorrelation using the two test, we find it desirable to examine the residuals visually to ensure the absence of any residual patterns that may affect the accuracy and validity of the model in Figure B.3. The figure also shows and confirms that there is no pattern in the ACF plot.

Heteroskedasticity Analysis: We also attempt to check the presence of heteroskedasticity in the residuals to detect whether the variance of the estimated residuals changes systematically over time. The ARCH (Autoregressive Conditional Heteroskedasticity) test is applied for heteroskedasticity to the residuals of the VAR mdel to examine the presence of conditional heteroskedasticity in the time series data.[3] The ARCH test's results is shown in Figure B.3 for the all the variables. The plot indicates no heteroskedasticity in the residuals of the VAR model.

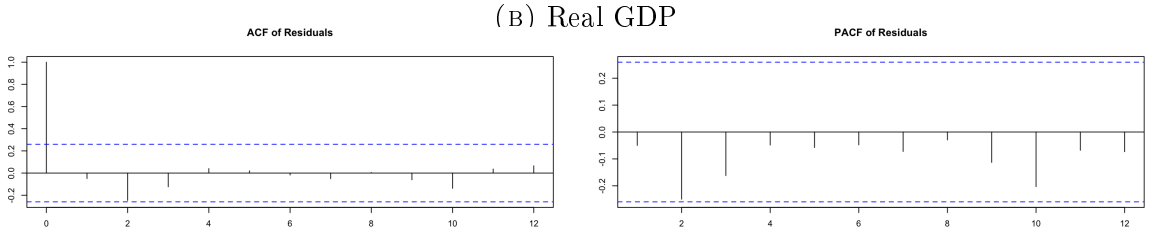
[3]The ARCH model is a time series model for capturing conditional heteroskedasticity, which allows for the variance of the current innovation to be modeled based on past observations or their conditional variances.

FIGURE B.3: ARCH (Autoregressive Conditional Heteroskedasticity) Test for Heteroskedasticity

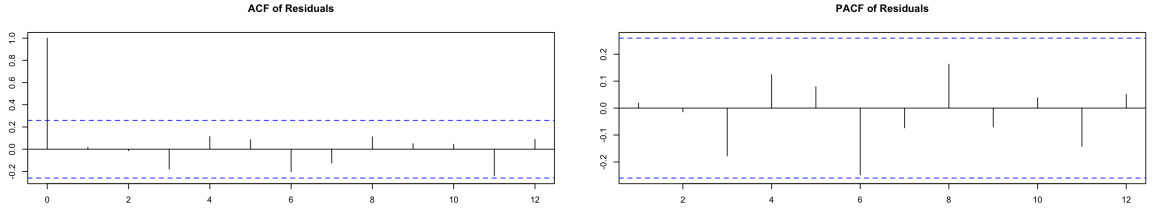
(A) Repo Rate



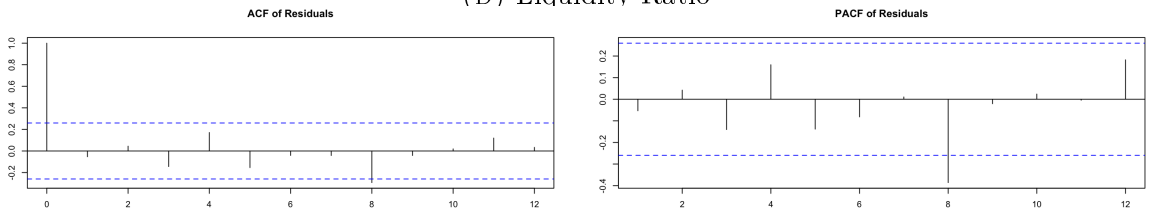
(B) Real GDP



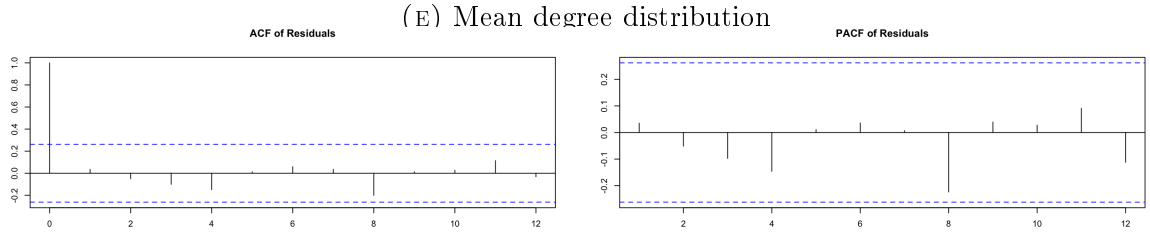
(C) Network Index



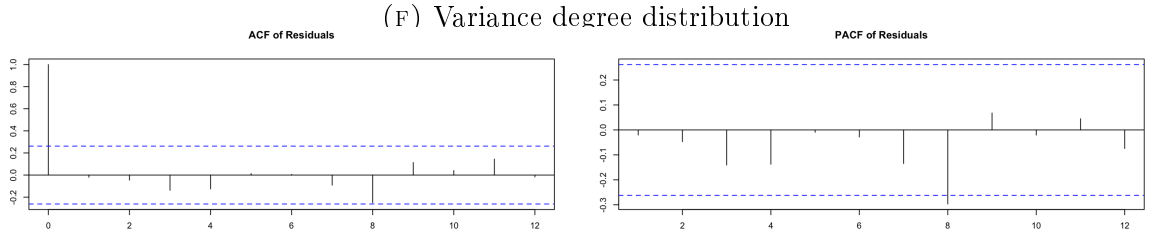
(D) Liquidity Ratio



(E) Mean degree distribution



(F) Variance degree distribution



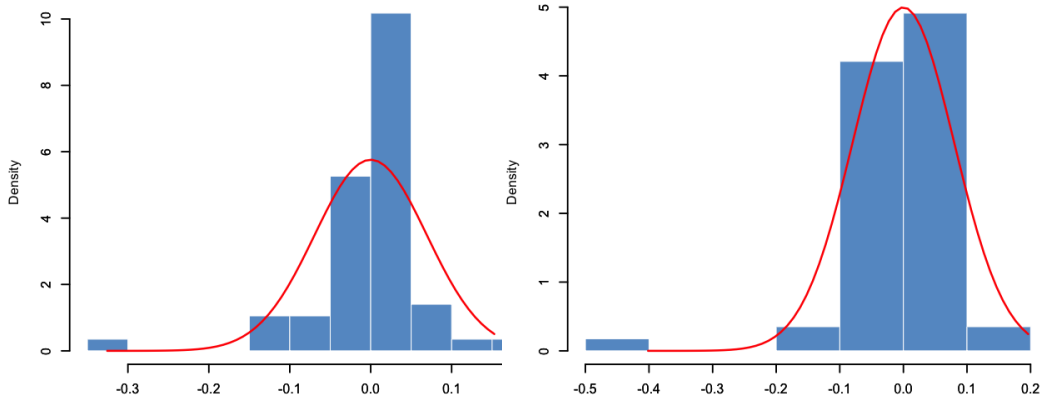
Note: Figure represents the ACF and PACF of residuals for the first 12 lags of VAR model to check the heteroskedasticity of the residuals.

Normality Analysis: This step examines the distributional properties of the residuals to assess whether it is normal. The histogram of the residuals in Figure B.4 shows skewness in the

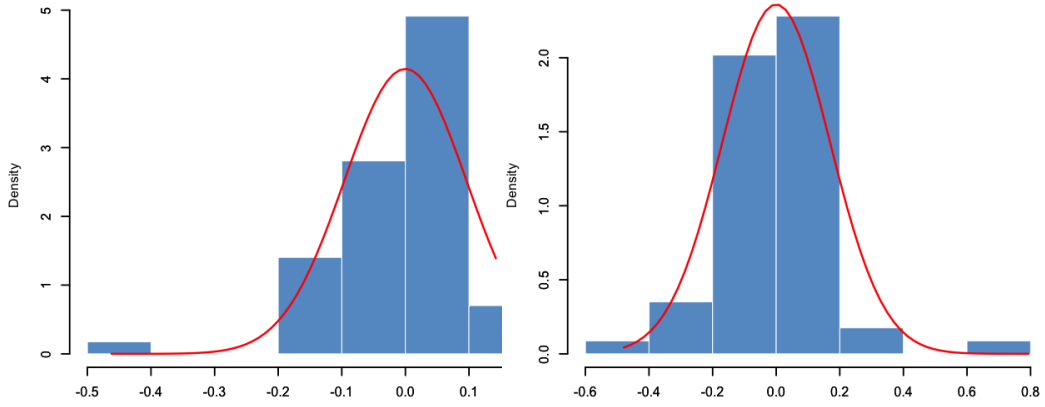
tale of the histogram which implies the presence of slight non-normality. To overcome this issue, we apply two approaches: first, we employ the non-parametric Generalized Method of Moments (GMM) method instead of traditional linear models for estimating VAR parameters to relax the normality assumption. GMM does not require specifying the distribution of the errors and accommodate non-normal error distributions by allowing for more robust and efficient parameter estimation while relaxing some of the restrictive condtions (Hansen, 1982; Hall, 2004). Secondly, we employ Bootstrap robust methods for inference, which provides more reliable estimates and confidence intervals even in the presence of non-normality (Bickel and Freedman, 1984; Berkovits et al., 2000).

FIGURE B.4: Histogram of the Residuals

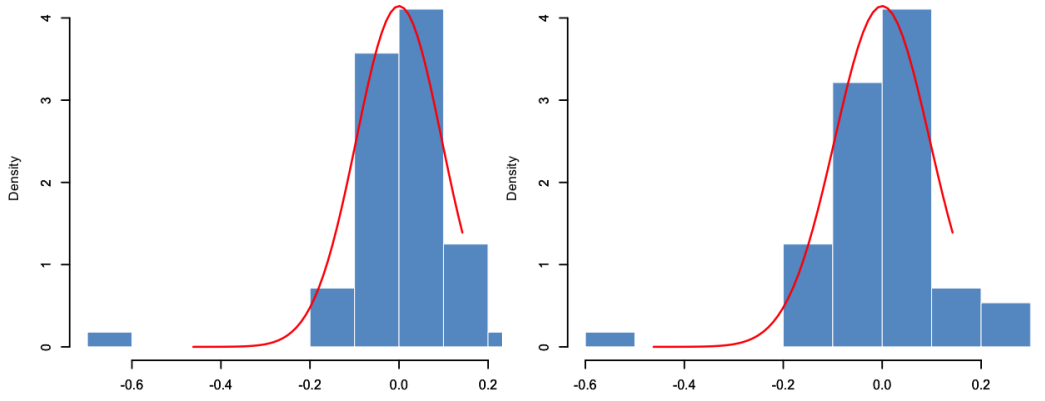
(A) Repo Rate (B) Real GDP



(C) Network Index (D) Liquidity Ratio



(E) Mean Digree Distribution (F) Variance Digree Distribution



Note: Figure represents the histograms of residuals taken from VAR model to check the normality condition.

B.4.4 Sensitivity Analysis

B.4.4.1 Model Parameters

B-model:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.11} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.20} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.08} \end{pmatrix} \tag{B.10}$$

AB-model:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \underset{(0.46)}{0.94} & 1 & 0 & 0 \\ \underset{(0.0009)}{-0.06} & \underset{(0.039)}{0.013} & 1 & 0 \\ \underset{(0.001)}{-0.28} & \underset{(0.004)}{-0.24} & \underset{(0.19)}{-0.012} & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.119} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.17} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.07} \end{pmatrix} \tag{B.11}$$

Mean degree distribution:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.15} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.19} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.09} \end{pmatrix} \tag{B.12}$$

Variance degree distribution:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.15} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.20} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.09} \end{pmatrix} \tag{B.13}$$

B.4.4.2 Model Covariance Matrix

We examine the symmetric covariance matrix B.14 (multiplied by 100), denoted as Σ_e, between the error terms to understand the relationships between endogenous variables and the transmission mechanisms of shocks in the system. For the interest rate/output/liquidity ratio/network system, the innovation or white noise covariance matrix in the system is,

$$\Sigma_e = \begin{pmatrix} 1.42 & -1.34 & 0.11 & 0.08 \\ \bullet & 4.25 & -0.15 & 0.64 \\ \bullet & \bullet & 0.91 & 0.01 \\ \bullet & \bullet & \bullet & 0.71 \end{pmatrix} \tag{B.14}$$

where each element in Σ_e represents the covariance between the error terms of two respective variables. The diagonal elements of Σ_e denote the variances of the individual error terms while the off-diagonal elements show the covariances between different pairs of error terms. The square roots of the variances represent the magnitude of the innovations, so we follow up on a structural shock of $\sqrt{4.25} = 2.06$ (tracing an unexpected two standard deviation increase) in liquidity ratio since the standard deviation of e_{2t} is 2.06. The high size of the standard deviation for the liquidity ratio 2.06 reflects the high magnitude of the innovations within the system. The innovation related to the network effect, represented by $\sqrt{1.42}$, is the second highest among the variables. The GDP and repo rate with $\sqrt{0.91}$ and $\sqrt{0.71}$ show mildest innovations in the system, implying that GDP and the repo rate are less sensitive to sudden changes.

Equation Σ_e also reports that the strongest correlation is available between $e_{1,t}$ and $e_{2,t}$ with -1.34, showing a very strong positive correlation between the network effect and remaining sources of liquidity. The correlation 0.64 is the second strong correlation between the quick ratio and the repo rate. Other off-diagonal elements report relatively weak correlation between the innovations. GDP and the network effects, for instance, shows the lowest correlation in the system, which reflects the lack of significant correlation between certain pairs of error terms, such as between the GDP and the network effects (0.01), implies that a shock in GDP/network effect may not be accompanied by a shock in network effect/GDP in the same period.[4]

B-model:

$$\Sigma_e = \begin{pmatrix} 0.013 & -0.0129 & 0.0009 & 0.001 \\ \bullet & 0.041 & -0.0005 & 0.004 \\ \bullet & \bullet & 0.009 & -0.0004 \\ \bullet & \bullet & \bullet & 0.0068 \end{pmatrix} \tag{B.15}$$

AB-model:

$$\Sigma_e = \begin{pmatrix} 0.014 & -0.013 & 0.001 & 0.0008 \\ \bullet & 0.042 & -0.0014 & 0.006 \\ \bullet & \bullet & 0.009 & 0.0008 \\ \bullet & \bullet & \bullet & 0.007 \end{pmatrix} \tag{B.16}$$

Mean degree distribution:

[4] In Appendix B.4.4.2, we present the robustness check for alternative scenarios and different network indices. Notably, the variance-covariance matrices for the B model, AB model, mean degree, and variance degree exhibit remarkable similarity.

$$\Sigma_e = \begin{pmatrix} 0.024 & -0.025 & 0.0007 & 0.0003 \\ \bullet & 0.038 & -0.0006 & 0.0042 \\ \bullet & \bullet & 0.009 & -0.0003 \\ \bullet & \bullet & \bullet & 0.008 \end{pmatrix} \tag{B.17}$$

Variance degree distribution:

$$\Sigma_e = \begin{pmatrix} 0.023 & -0.024 & -0.0012 & 0.0001 \\ \bullet & 0.041 & -0.0003 & 0.003 \\ \bullet & \bullet & 0.009 & -0.0003 \\ \bullet & \bullet & \bullet & 0.008 \end{pmatrix} \tag{B.18}$$

B.4.4.3 Forecast Error Variance Decomposition (FEVD)

TABLE B.7: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/network effect system for AB model

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Network effect	Quick ratio	GDP	Repo rate
Repo rate	1	0.006	0.24	0.0002	0.74
	2	0.09	0.25	0.017	0.63
	3	0.08	0.25	0.02	0.63
	4	0.08	0.24	0.05	0.61
	5	0.08	0.24	0.08	0.59
	10	0.10	0.22	0.11	0.54
	20	0.11	0.22	0.12	0.53
GDP	1	0.009	0.00	0.98	0.00
	2	0.01	0.04	0.92	0.01
	3	0.01	0.04	0.92	0.01
	4	0.02	0.06	0.87	0.03
	5	0.06	0.07	0.83	0.02
	10	0.14	0.07	0.75	0.02
	20	0.14	0.07	0.76	0.02
Quick ratio	1	0.30	0.69	0.00	0.00
	2	0.37	0.62	0.00	0.00
	3	0.43	0.55	0.00	0.01
	4	0.43	0.54	0.009	0.01
	5	0.44	0.53	0.011	0.01
	10	0.47	0.49	0.02	0.01
	20	0.49	0.46	0.02	0.01
Network effect	1	1.00	0.00	0.00	0.00
	2	0.99	0.00	0.00	0.00
	3	0.98	0.00	0.01	0.00
	4	0.95	0.00	0.02	0.017
	5	0.95	0.00	0.02	0.01
	10	0.90	0.04	0.02	0.02
	20	0.90	0.04	0.03	0.02

Note: Table reports Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/quick ratio/network effect system for 20 time periods.

TABLE B.8: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/mean degree system

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Mean degree	Quick ratio	GDP	Repo rate
Repo rate	1	0.00	0.00	0.00	1.00
	2	0.00	0.002	0.004	0.99
	3	0.0004	0.002	0.004	0.99
	4	0.0005	0.006	0.017	0.97
	5	0.0006	0.01	0.018	0.96
	10	0.0009	0.021	0.02	0.95
	20	0.002	0.022	0.02	0.94
GDP	1	0.00	0.00	1.00	0.00
	2	0.002	0.006	0.95	0.03
	3	0.006	0.008	0.94	0.03
	4	0.006	0.072	0.86	0.06
	5	0.004	0.12	0.82	0.04
	10	0.04	0.13	0.75	0.06
	20	0.04	0.14	0.74	0.06
Quick ratio	1	0.00	1.00	0.00	0.00
	2	0.13	0.86	0.001	0.001
	3	0.16	0.81	0.001	0.01
	4	0.19	0.76	0.02	0.017
	5	0.26	0.68	0.02	0.03
	10	0.28	0.63	0.03	0.04
	20	0.31	0.60	0.036	0.04
Mean degree	1	1.00	0.00	0.00	0.00
	2	0.95	0.019	0.02	0.003
	3	0.92	0.03	0.029	0.003
	4	0.90	0.03	0.05	0.003
	5	0.90	0.03	0.05	0.005
	10	0.89	0.039	0.06	0.006
	20	0.89	0.04	0.059	0.006

Note: Table reports Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/quick ratio/mean degree system for 20 time periods.

TABLE B.9: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/variance degree system

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Variance degree	Quick ratio	GDP	Repo rate
Repo rate	1	0.00	0.00	0.00	1.00
	2	0.009	0.0001	0.002	0.98
	3	0.009	0.001	0.003	0.98
	4	0.009	0.007	0.02	0.95
	5	0.009	0.01	0.03	0.94
	10	0.016	0.014	0.04	0.92
	20	0.02	0.019	0.05	0.90
GDP	1	0.00	0.00	1.00	0.00
	2	0.001	0.002	0.96	0.03
	3	0.004	0.002	0.95	0.03
	4	0.004	0.06	0.88	0.05
	5	0.003	0.11	0.84	0.039
	10	0.03	0.14	0.77	0.05
	20	0.03	0.15	0.76	0.05
Quick ratio	1	0.00	1.00	0.00	0.00
	2	0.07	0.91	0.002	0.001
	3	0.10	0.87	0.007	0.008
	4	0.13	0.83	0.011	0.019
	5	0.18	0.75	0.034	0.03
	10	0.19	0.70	0.05	0.04
	20	0.21	0.67	0.06	0.04
Variance degree	1	1.00	0.00	0.00	0.00
	2	0.97	0.01	0.02	0.002
	3	0.93	0.02	0.03	0.0029
	4	0.84	0.049	0.089	0.01
	5	0.80	0.07	0.09	0.03
	10	0.78	0.13	0.05	0.03
	20	0.78	0.13	0.05	0.029

Note: Table reports Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/quick ratio/variance degree system for 20 time periods.

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