

AYÇA TOPALOĞLU BOZKURT

BANK NETWORKS IN TÜRKİYE

Bilkent University

BANK NETWORKS IN TÜRKİYE

A Ph.D. Dissertation

by
AYÇA TOPALOĞLU BOZKURT

Department of
Management
İhsan Doğramacı Bilkent University
Ankara
November 2023



To Defne and Melih

BANK NETWORKS IN TÜRKİYE

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

AYÇA TOPALOĞLU BOZKURT

In Partial Fulfillment of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY IN MANAGEMENT

THE DEPARTMENT OF MANAGEMENT
İHSAN DOĞRAMACI BİLKENT UNIVERSITY
ANKARA

November 2023

BANK NETWORKS IN TÜRKİYE
by Ayça Topaloğlu Bozkurt

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Business Administration.

Süheyla Özyıldırım
Advisor

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Business Administration.

Erol Taymaz
Examining Committee Member

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Business Administration.

Hakan Berument
Examining Committee Member

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Business Administration.

Ahmet Şensoy
Examining Committee Member

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Business Administration.

İlkay Şendeniz Yüncü
Examining Committee Member

Approval of the Institute of Economics and Social Sciences

Refet S. Gürkaynak
Director

ABSTRACT

BANK NETWORKS IN TÜRKİYE

Topaloğlu Bozkurt, Ayça
Ph.D. in Department of Management
Supervisor: Assoc. Prof. Dr. Süheyla Özyıldırım

November 2023

This thesis analyzes the loan network and cross-border network of banks in Türkiye. The impacts of two developments during the studied period between 2007-2019 that significantly affected the credit market, the increase in Treasury-backed guarantees and the exchange rate shock, on these bank networks were also investigated. In the first study, we introduce a novel measure of bank interconnectedness. Using more than 44 million loan observations during the period of 2007–2016, we construct a projected loan network that emerges from the banks’ lending to common firms. Then, we investigate the relation between banks’ loan portfolio riskiness and their connectedness. Our findings suggest that highly connected banks seem to manage their overall portfolio risk better. In the ends of the first quarter of 2017, the Treasury support for the sureties given by the Credit Guarantee Fund of Türkiye (CGF) increased to 12.5-fold and affected credit market significantly. In the third chapter, We investigate whether investor reactions to the announcement of the increase in Treasury support in CGF guarantees are in line with the stated aim of the program. We find that investors perceived the increase in Treasury support to benefit both firms and financial institutions. In the fourth chapter, extending our sample period in the first study, we investigate how CGF schemes changed the bank-loan network

in Türkiye. We also find that CGF schemes support the negative relation between the bank connectedness and loan portfolio riskiness. On the other hand, banks' loan portfolio riskiness increases with the schemes. Finally, considering the impact of currency shock in 2018 on the banking system, in the last chapter we study the cross-border bank network in Türkiye. We find that the currency shock negatively affects the cross-border network and its impact on cross-border borrowings changes based on lender banks' country origin, showing the importance of diversification of funding partners.

Keywords: Bank Loan and Cross-Border Networks, Currency Shock, Cross-Border Lending, Loan Portfolio Riskiness, Public Credit Guarantee Schemes

ÖZET

TÜRKİYE BANKA AĞLARI

Topaloğlu Bozkurt, Ayça
Doktora, İşletme
Tez Danışmanı: Doç. Dr. Süheyla Özyıldırım

Kasım 2023

Bu tez, Türkiye'deki bankaların kredi ağlarını ve ülkeler arası ağlarını analiz etmektedir. Ayrıca, tezin incelediği 2007-2019 dönemi içinde meydana gelen ve kredi piyasasını önemli ölçüde etkileyen iki gelişmenin, Hazine destekli kefaletlerin artırılması ve kur şokunun, söz konusu ağlar üzerindeki etkileri de araştırılmıştır. İlk çalışmada, bankalar arası bağlantılılığı gösteren yeni bir ölçüm geliştirilmiştir. 2007-2016 döneminde 44 milyondan fazla kredi gözlemi kullanılarak, bankaların ortak (aynı) firmalara verdikleri kredilere dayalı izdüşümsel bir kredi ağı oluşturulmuştur. Ardından, bankaların kredi portföy riskliliği ile bağlantılılıkları arasındaki ilişki araştırılmıştır. Bulgularımız, bağlantılılık düzeyi yüksek olan bankaların genel portföy riskini daha iyi yönettiklerini gösteriyor. 2017 yılı ilk çeyreği sonlarında, Türkiye Kredi Garanti Fonu (KGF) tarafından verilen kefaletlere Hazine desteğinin 12,5 katına çıkarılması, kredi piyasasını önemli ölçüde etkiledi. Üçüncü bölümde KGF kefaletlerindeki Hazine desteğinin artırılmasına ilişkin duyuruya yatırımcıların gösterdiği tepkilerin programın belirtilen amacı ile uygunluğu araştırılmıştır. Çalışmamız, yatırımcıların Hazine desteğindeki artışı, firmalar ile finansal kurumlara fayda sağlayacak bir gelişme olarak algıladığını gösteriyor. Dördüncü bölümde, ilk çalışmadaki örneklem dönemi genişletilerek, KGF programlarının Türkiye'deki banka-kredi ağı üzerindeki etkisi araştırıl-

mıştır. Çalışmamız, KGF programlarının, banka bağlantılılığı ile kredi portföyü riskliliği arasındaki negatif ilişkiyi desteklediğini de bulguluyor. Öte yandan bahsigeçen programın bankaların kredi portföy riskliliğini de arttırdığı görülmektedir. Son olarak 2018 yılındaki kur şokunun bankacılık sistemi üzerindeki etkisi göz önünde bulundurularak, Türkiye’deki bankaların ülkeler arası ağları incelenmiştir. Çalışmamıza göre, kur şoku ülkeler arası ağları olumsuz etkilemiştir. Ayrıca, kur şokunun yabancı bankalardan borçlanma üzerindeki etkisi, söz konusu bankaların merkezlerinin bulunduğu ülkeye göre farklılık göstermektedir. Bu durum, finansman ülke paydaşlarının çeşitlendirilmesinin önemini ortaya koymaktadır.

Anahtar Kelimeler: Banka Kredi ve Ülkeler Arası Ağları, Kamu Kredi Garanti Programları, Kredi Portföy Riski, Kur Şoku, Ülkeler Arası Borç Verme

ACKNOWLEDGEMENTS

I would like to express my gratitudes to the people without whom my PhD journey would not have been possible.

First and foremost, I would like to express my deepest gratitude to my supervisor, Assoc. Prof. Dr. Süheyla Özyıldırım for her support from the very beginning to end. This PhD journey would not have been possible without her guidance, encouragement and understanding. Her experience and motivation in academic studies always kept my curiosity and desire to learn alive, and challenged me to improve myself.

I'm extremely grateful to Assoc. Prof. Dr. Başak Tanyeri for her support during the article publishing process which was very critical for my graduation. Besides, I would like to thank for enabling me to take the Seminar in Corporate Finance course by her in which she demonstrated very instructive, impressive and extraordinary performance.

I would like to thank to the members of my dissertation committee, Prof. Dr. Erol Taymaz and Assoc. Prof. Dr. Ahmet Şensoy for their valuable time, suggestions, constructive critics and guidance throughout my dissertation progress. Moreover, I am grateful to Prof. Dr. Hakan Berument and Assoc. Prof. Dr. İlkey Şendeniz Yüncü for accepting to serve as a member of my dissertation examination committee, and for their valuable suggestions.

I would like to express my gratitude to İ.D. Bilkent University for the scholarship and educational opportunities it provides, and also to the members of the Faculty

of the Business Administration for their positive attitudes, insights and contributions throughout my doctoral studies. In addition, I would like to express my special thanks to Remin Tantoğlu, graduate program coordinator of the Faculty, for her kind and constant assistance. I thank to İpek Kamoy, administrative stuff of the Faculty, for her timely support in our correspondence with the Central Bank and the University.

Words cannot express my gratitude to Tuba Pelin Sümer, who never spared her personal and professional support during my doctoral program and even before. Studying with her have always been very instructive and peaceful for me. In addition, I would like to extend my sincere thanks to Alper Ali Hekimoğlu, whose personal and professional support I have always felt.

In addition, I would like to thank to my friends with whom I had the opportunity to study in finance for their valuable contributions especially during the qualification process; namely Ezgi Alp, İdil Ayberk, Utku Bora Geyikçi and Süleyman Serdengeçti. Besides, I would thank to my colleagues from Central Bank of the Republic of Türkiye; Eda Gülşen and Ahmet Gülveren for their special supports during my dissertation process.

I would like to express my gratitude to the Central Bank of the Republic of Türkiye where I have been honored to be an employee for 14 years for improving my knowledge and experience, and the opportunities provided me during this PhD journey.

I would like to express my deepest gratitude to my big family for their moral support, encouragement, understanding, and patience. I would like to thank my father Rafet Topaloğlu, my mother Naime Topaloğlu, my mother-in-law Rüvide Bozkurt and my cousin Fulden Cihan, my sisters Pınar Karali, Gökçe Öntürk and my brother-in-law Özgür Öntürk.

This endeavor would not have been possible without the love of my husband and my daughter. I would like to express my endless gratitude to my beloved husband Melih, who made my life easier in every aspect with his endless patience and support. I am thankful to shining sun of my life, Defne for energizing me with her endless love.



TABLE OF CONTENTS

ABSTRACT	iii
ÖZET	v
ACKNOWLEDGEMENTS	vii
TABLE OF CONTENTS	x
LIST OF TABLES	xii
LIST OF FIGURES	xiv
CHAPTER I: INTRODUCTION	1
1.1 Overview	1
CHAPTER II: BANK-LOAN NETWORK	6
2.1 Introduction	6
2.2 Data and Banks' Loan Network	9
2.2.1 Data	11
2.2.2 Construction of Banks' Loan Network	13
2.3 Empirical Analysis	24
2.3.1 Additional Results and Robustness Tests	30
2.4 Conclusion	34
CHAPTER III: MARKET REACTIONS TO THE TREASURY-BACKED CREDIT GUARANTEES	49
3.1 Introduction	49
3.2 Background on the Credit Guarantee Fund of Türkiye	51
3.3 Research Method	52

3.4	Results	54
3.5	Conclusion	56
CHAPTER IV: HOW DID CREDIT GUARANTEE FUND SUPPORTS AFFECT THE BANK-LOAN NETWORK?		58
4.1	Introduction	58
4.2	Literature Review	62
4.3	Data	65
4.4	Bank Loan Network After CGF Supports	66
4.5	Empirical Results	72
4.6	Conclusion	75
CHAPTER V: CROSS-BORDER BANK NETWORK		79
5.1	Introduction	79
5.2	Data and Methodology	84
5.2.1	Data	84
5.2.2	Construction of Cross-Border Network	88
5.2.3	Empirical Strategy	92
5.2.4	Sub-samples	93
5.3	Empirical Results	95
5.3.1	Estimations Using Macro-Level Data	96
5.3.2	Estimations Using Micro-Level Data	100
5.4	Conclusion	106
CHAPTER VI: CONCLUSION		113
REFERENCES		116
APPENDIX		126

LIST OF TABLES

2.1	Number of Loan Transactions and Unique Firms	12
2.2	Summary Statistics of Weighted Degree Measures Across Banks . . .	26
2.3	Weighted Degree Measures by Banks' Size Groups	27
2.4	Summary Statistics of the Variables Used in the Baseline Model . . .	29
2.5	Estimation Results of the Baseline Model	36
2.6	Estimation Results by Loan Size Groups	37
2.7	Estimation Results of the Baseline Model Controlling for Multiple Borrowing	39
2.8	Estimation Results by Loan Size Groups Controlling for Multiple Bor- rowing	40
2.9	Estimation Results for the Probability of Default of Loans Borrowed by Firms	42
2.A1	Mean Comparisons of the Weighted Degree Centrality Measure Among Bank Clusters	43
2.A2	List of Variables	44
2.A3	Summary Statistics for the Variables Used in the Baseline Model . . .	45
2.A4	Pairwise Pearson's Correlation Coefficients	46
2.A5	Tests for Unit Roots in Level - Individual Effects	48
3.1	Cumulative Abnormal Returns Around the Announcement Day in the Full Sample	55

3.2	Cumulative Abnormal Returns Around the Announcement Day in Industry	
	Sub-samples	55
4.1	Impact on CGF Schemes on Weighted Degree Across Bank-Size Groups	68
4.2	Impact of CGF Schemes on Weighted Degree Across Bank-Business	
	Groups	69
4.3	Impact on CGF Schemes on Weighted Degree Across Bank-Connectedness	
	Groups	70
4.4	Estimation Results of the Baseline Model	71
4.5	Estimation Results of the Baseline Model Controlling for Multiple	
	Borrowing	76
5.1	The Impact of FX Shock on Banks' Cross-Border Network	96
5.2	The Impact of FX Shock on Banks' Cross-Border Network Across	
	Banks' Cross-Border Connectedness	98
5.3	The Impact of FX Shock on Banks' Cross Border Network Across	
	Banks' Business Types	99
5.4	Counterparty Level Estimations: The Impact of FX Shock on Banks'	
	Cross-Border FX Borrowings	101
5.5	The Impact of FX Shock and Affiliated Resident Banks on Banks'	
	Cross-Border FX Borrowings	103
5.6	The Impact of FX Shock, Affiliation and Counterparty Bank's Head-	
	quarter Country Group on Banks' Cross-Border FX Borrowings . . .	105
5.A1	Pairwise Correlations	108
5.A2	Descriptive Statistics Before and After FX Shock	108
5.A3	Descriptive Statistics Based on Banks' Business Types	109
5.A4	Descriptive Statistics Based on Banks' Connectedness	110

LIST OF FIGURES

2.1	The Share of Firms Borrowing from Multiple Banks	9
2.2	Bipartite and Projected Network	16
2.3	Projected Loan Network of Banks as of December 2008	20
2.4	Projected Loan Network of Banks as of December 2009	21
2.5	Projected Loan Network of Banks as of December 2012	22
2.6	Projected Loan Network of Banks as of December 2015	23
4.1	The Share of Firms Borrowing from Multiple Banks	59
4.2	The Changes in the Share of Firms Borrowing from Multiple Banks After CGF Supports	60
4.3	Projected Loan Network of Banks as of December 2016 and 2017 . .	67
5.1	Exchange Rate of Turkish Lira Against US Dollar	80
5.2	BIS Locational Statistics	81
5.3	FX Lending and FX Borrowing of Banks	85
5.4	Composition of Cross-Border FX Borrowings	88
5.5	Average Strength Centrality and Degree of Banks	89
5.6	Bipartite Cross-Border Network of Resident Banks	90
5.7	Strength Centrality Across Banks' Connectedness Groups	91
5.8	Strength Centrality Across Banks' Business Types	94
5.9	FX Loan Borrowings of Resident Banks Across Headquarter Country Grouping of the Counterparty Banks	95

5.A1 The Relation Between FX Loans Extended by Resident Banks to Do-
mestic Firms and FX Cross-Border Borrowings 111

5.A2 Degree Centrality Across Banks’ Connectedness Groupings 112



CHAPTER I

INTRODUCTION

1.1. Overview

Global financial crisis has demonstrated the vitality of measuring systemic risk for the healthy functioning of financial system. In this vein, the determination of the networks among the banks has gained importance. Bank networks enable to detect the vulnerabilities in the banking system and to measure the response of the financial system to distress periods.

The literature highlights three different network channels creating systemic risk in banking sector: direct channel of interbank lending, indirect channel of common asset holdings; and indirect channel originated from non-financial firms. There is relatively a large number of studies investigating interbank networks (Freixas et al., 2000; Boss et al., 2004; Nier et al., 2007; Gai and Kapadia, 2010, 2011; Georg, 2013; Van Lelyveld, 2014; Sachs, 2014) and indirect channel of common assets (Acharya, 2009; Allen et al., 2012; Caballero and Simsek, 2013; Tian et al., 2013; Greenwood et al., 2015; Cai et al., 2018; Pichler et al., 2021, Roncoroni et al., 2021). There is, however, relatively paucity of studies focusing indirect channel originated from non-financial firms due to a lack of granular data (Li et al., 2019; Poledna et al., 2018; Silva et al., 2018). The studies investigating the interaction of the indirect channels of commonality and non-financial firms are even less (Abbassi

et al., 2017; Biswas and Gomez, 2018; Li et al., 2020), though the systemic risk emanating from firms' borrowing from banks is much higher than from interbank loans (Lux, 2016; Poledna et al., 2018).

In this thesis, we first study one of the components of the indirect channel, that of the loan network of banks' emerging from their lending to same firms. In this chapter, our contribution to literature is twofold: First, we introduce a weighted novel measure of bank interconnectedness by constructing a projected loan network based on relations between banks and their common firms using more than 44 million loan observations during the period of 2007–2016. To our knowledge, this is the largest financial network which includes all bank-firm loan transactions, i.e., population data that has not been studied up to now. Second, contrary to prior studies of connectedness in the literature, we focus on the banks' portfolio riskiness rather than systemic risk. In particular, we investigate the impact of connectedness rooted in common borrower's on banks' overall portfolio riskiness. Our findings show that banks' portfolio riskiness decreases with connectedness, even when controlling for the impacts of loan size and multiple borrowing. Moreover, we find that the probability of loan default is higher for highly connected banks compared to weakly connected ones. These findings suggest that highly centralized banks seem to manage their overall portfolio risk better.

The Turkish Treasury decided to increase the support of the Treasury backed sureties given by Credit Guarantee Fund of Türkiye (CGF) more than ten folds to stimulate economic activity by alleviating financing constraints toward the ends of 2016. The Treasury backed CGF guarantees, one of the largest of its kind among the OECD countries (OECD, 2019), started to be implemented at the end of the first quarter of 2017 and affected the credit market predominantly. In the next chapter, we investigate whether investor reactions to the announcement of the increase in Treasury support in CGF guarantees are in line with the stated aim of

the program. Our third chapter contributes to the literature by focusing on how change in investor expectations was reflected in stock returns on the announcement date. We find that the nine-day cumulative abnormal returns prove positive and significant around the announcement of the increase in Treasury support. Investors ex-ante perceived the benefits of the program to outweigh the costs. The positive stock market reaction suggests that the government succeeded in improving investor expectations. In addition, the ex-post outcomes of firms receiving CGF-guaranteed loans corroborate the ex-ante positive investor reaction to the increase in Treasury support. The growth rate of total commercial loans, which accelerated in March 2017 via the supports, exceeded the average rate of growth in previous years. Güngör and Sümer (2018) report that about one-third of the CGF loan beneficiaries received loans for the first time. The proportion of firms securing loans for the first time suggests that the policy aim of providing funds to credit-constrained Turkish firms proved successful. Furthermore, Akçiğit et al. (2021) found that firms receiving CGF-guaranteed loans enjoyed higher sales, increased employment, and decreased default probability relative to a control group that did not receive CGF loans. Hence, in the following chapter we study the impact of CGF schemes, which affected loan markets predominantly, on bank-loan network.

In the fourth chapter, we extend our sample period to study how public loan guarantee schemes changed the bank-loan network in Türkiye. CGF schemes deserve special attention considering the fact that they had a significant impact on the credit market, affecting both banks and firms (Akçiğit et al., 2021; Güngör and Sümer, 2018). The total volume of the banking sector’s outstanding credits was increased by 10 percent via the introduction of Treasury backed CGF guarantees as of March 2017. In addition, CGF schemes provided a substantial amount of surety not only for SMEs but also large firms in Türkiye. More than 75 percent of

Treasury-backed CGF guarantees in volume were given to SMEs. Nonetheless, the amount guaranteed was also very high for large firms, as it constituted almost 25 percent of the credit guarantees of 200 billion TL. The second CGF package, which amounts to 55 billion TL of guarantee backed by the Treasury including the repayments of the first package, is launched in January 2018. We show that though the share of loans borrowed by firms with multiple banks slightly increased, the share of these firms over total firms decreased amid the Treasury support of CGF guarantees. Based on these information, we question the impact of CGF schemes on the loan network of banks in Türkiye. First, we investigate whether these CGF schemes have resulted in a significant change in the bank loan network. Moreover, we study whether the impact of loan centrality on bank portfolio riskiness changed with these schemes. Our empirical results show that the impact of CGF is heterogeneous across banks' groups. CGF schemes significantly increases the connectedness of large banks and small banks, but they do not have a significant impact on mid-size banks. Moreover, the connectedness of state-owned banks and private domestic banks is significantly increased with the CGF schemes. We also find that CGF schemes support the negative relation between the bank connectedness and loan portfolio riskiness that we show in the first chapter. On the other hand, banks' loan portfolio riskiness increases with these publicly supported schemes.

After studying the one of the components of the indirect channel creating systemic risk in banking sector via bank loan network, in the last chapter, we study the one of the components of the direct channel of interbank cross-border lending. Since the implementation of the inflation targeting regime in 2006 until the end of the studied period, Türkiye experienced the largest depreciation in the Turkish lira during August of 2018. Considering the impact of the currency shock on the Turkish banking system, in the fifth chapter, we exploit the currency shock in 2018

as a natural experiment to explore whether, and how, bank interconnectedness evolved after the exchange rate shock. A number of studies explore the effects of global real and financial shocks on cross-border banking activities, including the impact of 2008-2009 financial crisis, euro debt crisis shock and US monetary policy shocks on the capital flows to advanced and emerging economies (Reinhardt and Riddiough, 2015; Castrén and Rancan, 2014; Albertazzi and Bottero, 2014; Claessens, 2017; Cerutti et al., 2017; Alper et al., 2020; and Abbassi et al., 2022). In contrast, we focus on the impact of a local crisis, a large currency depreciation, on FX borrowings of resident banks from a network perspective. We first construct the cross-border network of banks employing a confidential loan-level data during 2012–2019 in Türkiye. Then we analyze the impact of the exchange rate shock (a rapid depreciation of the local currency) on the foreign currency (FX) borrowings of the resident banks via cross-border network. Our bank level empirical findings show that currency shock has a significant and negative impact on cross-border interbank networks. The shock has strongest effect on the weakly connected banks as well as private commercial banks. The loan level empirical estimations show that affiliated foreign counterparties that support the amount of FX borrowings in normal times, do not accommodate the impact after the shock. Finally, we find that the impact of the exchange rate shock on cross-border borrowing changes based on lender banks’ country origin, showing the importance of diversification of funding partners.

CHAPTER II

BANK-LOAN NETWORK

2.1. Introduction

The global financial crisis in 2007/2008 demonstrated the vital importance of recognizing systemic risk early on. Allen and Babus (2009) emphasize that network approaches become particularly useful to explore the interconnected systems such as banks, where the fragility of the system may depend on the degree of connectivity among the banks. The literature identifies three network channels that create systemic risk. These are the propagation of risk arising from the impact of the default of one bank on the other banks (direct channel of interbank lending); the impact of common asset holdings, such as losses from the same firms or common risk exposures captured by similar investment assets on banks' balance sheets (indirect channel of common asset holdings); and the propagation of credit risk originated from non-financial firms (indirect channel of firm-bank relations or firm-firm relations).

There is a relatively large number of studies investigating the impact of interbank networks on systemic risk (Freixas et al., 2000; Nier et al., 2007; Gai et al., 2011; Georg, 2013; Van Lelyveld, 2014). In addition, a number of papers theoretically examine how shocks are indirectly transmitted among financial institutions via common asset holdings (Acharya, 2009; Allen et al., 2012; Caballero and Simsek,

2013; Tian et al., 2013; Greenwood et al., 2015). However, there have been few studies thus far regarding common asset channel due to limited data availability (Cai et al., 2018; Pichler et al., 2021; Greenwood et al., 2015, Roncoroni et al., 2021). Among the common asset holding literature, papers focusing on the networks that emerge from lending to common firms are even more limited (Abbassi et al., 2017; Biswas and Gómez, 2018; Li et al., 2020). In this chapter, we explore one of the components of the indirect channel, that of the bank loan network of common assets emerging from banks lending to same firms, by using confidential and comprehensive data from the Turkish banking system that covers all bank-firm loan transactions between March 2007 and December 2016.

Abbassi et al. (2017) study the systemic risk arising from the indirect impact of common firms and common exposures of similar securities as well as from the direct interbank channel. They show that higher amounts of interbank exposure between two banks, or higher similarity in their loan portfolio, or higher assets associated with securities investments suggest higher realized interconnectedness. Liu et al. (2020) also investigate the impact of bank-firm relations on systemic risk but focus on both the direct lending relationships between them and the indirect channels by co-financing relationships and co-financed relationships. They construct a multi-layer multiplex networks of bank-firm relations for short term and long term maturities using the data from China. They apply DebtRank distributions to measure the major contributors to systemic risk in the banking sector.¹ To the best of our knowledge, only one theoretical paper by Biswas and Gómez (2018) shows that a solvency problem in one bank is transmitted to another if they lend to the same borrower. It is argued that the mechanism behind this transmission is based on the impact of decreasing incentives of the co-lending bank for monitoring the

¹DebtRank is a feed-back centrality measure by Battiston et al. (2012) to find out the systematically important nodes in a network. It measures the distress generated and spread from a node to the overall network. The higher the DebtRank of an initial node, the higher the impact of this node on the others in the network.

common borrowers when the co-lending bank is hit by a solvency shock.

Early studies show that systemic risk emanating from firms' borrowing from banks is much higher than from interbank loans (Lux, 2016; Poledna et al., 2018).² Our study contributes to the literature twofold: First, we introduce a weighted novel measure of bank interconnectedness by constructing a projected loan network based on overlapping contractual relations between banks and firms from 44 million bank-firm loan observations during the period of 2007–2016 in the Turkish banking system. Second, while prior studies of connectedness mostly focused on the systemic risk, we concentrate on the banks' individual credit risk and investigate the impact of connectedness rooted in common asset holdings on a bank's loan portfolio riskiness. We provide empirical evidence that more connected banks have lower overall loan portfolio riskiness, even when controlling for the impacts of loan size and multiple borrowing. Then, we empirically show that the bank loan network of borrower contractual relations offers some explanation about the credit portfolio riskiness of banks. Utilizing loan level analysis from more than five million loans, we document that the odds of default of the borrowing firm is higher for highly connected banks compared to weakly connected ones. Considering these contradictory empirical results from aggregated bank-level and transaction level analyses, our findings reveal that highly centralized banks are not granting to the firms that are more resilient, rather these banks manage their overall portfolio risk better.

Our study highlights that banks may have an incentive to increase their centrality to exploit the benefits of having borrower loan portfolios. While it is advantageous for banks to increase their connectedness, it may be disadvantageous for the banking system as whole to increase the contagion (Lux, 2016; Biswas and Gómez,

²Lux (2016) and Poledna et al. (2018) investigate the systemic risk in the financial system emerging from the contagion via bank-firm relations and interbank relations; Silva et al. (2018) study these networks as well as firm-firm interactions.

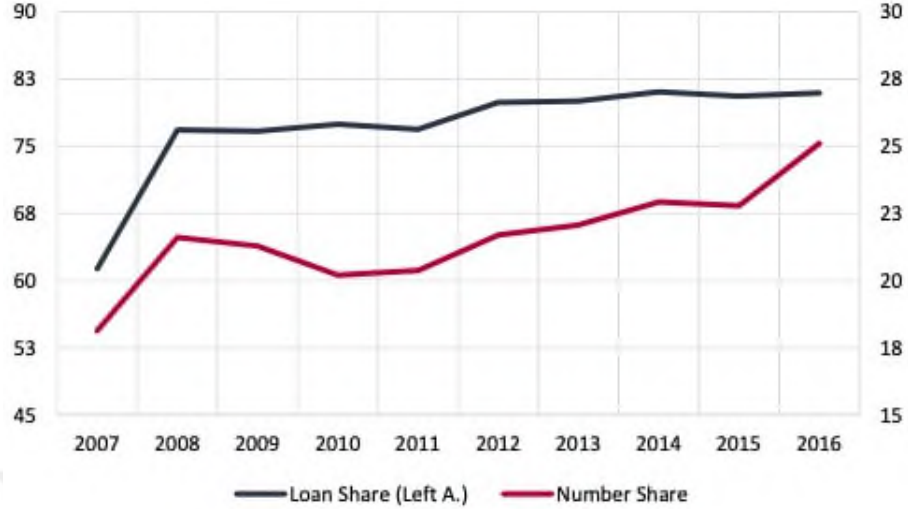


Figure 2.1: The Share of Firms Borrowing from More Than One Bank

Red line shows the share of firms borrowing from more than one bank over total firms (in percent, at right axis) and the black line shows the share of loans borrowed by firms with multiple banks (in percent, at left axis).

2018; Liu et al., 2020). The policy implication of our study is that the projected networks, based on the common borrowers of banks, will be of practical use for bank supervisors and central banks to monitor and measure the net benefits of the negative and positive externalities of an interconnected financial system and to ensure financial stability.

The outline of the chapter is as follows: Section 2 introduces the data, network methodology, and the novel weighted degree centrality measure. Section 3 presents the econometric analysis, the empirical findings, and robustness checks. Section 4 concludes the chapter.

2.2. Data and Banks' Loan Network

In this chapter, we use the confidential data on commercial loans from Türkiye over the period of 2007Q1 through 2016Q4. Bank lending is an important source of financing for both large firms and small and medium-sized enterprises (SMEs) in

Türkiye. Demirguc-Kunt et al. (2011) find that Türkiye is one of the market based countries as it has a low financial structure ratio (0.9 percent) which is calculated by the dividing the volume of private credit by banks by the market capitalization. In addition, Ongena and Şendeniz-Yüncü find that the number of banks that a firm has relationships with is 2.6 on average in 2008 for Türkiye, indicating that it is a bank-based country. Finally, Şendeniz-Yüncü (2020) documents that Türkiye has transitioned to a market oriented system from the bank-based system in 1995 when it has experienced a very rapid development of the stock market. On the other hand, its financial structure turned to market based system since 2012. Our population data shows that around 20–25 percent of the firms in Türkiye borrow from more than one bank, yet the volume of loans received by these firms constitutes 75 percent of all loans (Figure 2.1).³

As presented by Table 2.1, the commercial loan transactions across the bank-size group is not homogeneous.⁴ Table 2.1 reports that large banks hold more than 60 percent of loans during the sample period, while mid-sized banks and small banks hold 35 percent and almost 3.5 percent of the total loans transactions on average, respectively. Number of loan transactions varies widely across banks' business groups as well. For example, state-owned banks, particularly in more recent years, grant more loans than privately owned and foreign banks. Due to acquisition of one of the major private domestic banks by a foreign bank in 2015, the loan transactions by foreign-owned banks become higher than those by private-domestic banks. Development and investment banks are the bank group with the least loan transactions.

³Multiple lending structure varies across countries. Ongena and Smith (2000) document that single-bank relationships are relatively uncommon among European countries. Among sample of European firms, they find that the average number of banks is between 5 and 6. De Masi et al. (2011) show that firms have more multiple bank relations in bank-based countries such as Germany, Italy, and Japan in comparison to market-based countries such as the UK.

⁴Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets; the remaining banks are small banks.

2.2.1 Data

In the study, we use various databases to extract the topology of banks' commercial loan network and uncover the impact of network centrality on the overall credit riskiness of the banks. First, we use more than 44 million loan level observations from the “Loans by Customers” database of the Central Bank of the Republic of Türkiye (CBRT) and Banking Regulation and Supervision Agency (BRSA) to construct the bank-loan network. Our network is based on the common borrowing firms through which an indirect link between the lender banks is constructed. We call a firm a “common” firm if that firm borrows from more than one bank at the same time. We also use this database to calculate the ratio of non-performing loans, the number of common firms, and the volume of the loans of these firms as well as the all firms. This database covers all types of loans (commercial, housing, vehicle, and general-purpose loans) provided by all types of banks (deposit banks, development and investment banks, and participation banks) in Türkiye. We restrict the analysis to commercial loans to extract the loan network derived from the lending relationship between banks and firms. Our sample extends from March 2007 to December 2016 due to data quality concerns in the early periods. We end the sample in 2016 to avoid the possible impacts of accelerated credit expansion by the Treasury support for credit guarantee funds in March 2017.

In the data set, commercial loans are not unique in a given period for each firm-bank pair. For this reason, we aggregate the loan amounts at each period. However, before we create a unique account for each firm-bank pair, we apply various cleaning procedures: Observations with zero or a missing loan amount and a lack of grant date or maturity date are excluded. The loan accounts are unified according to the following algorithm: For each bank-firm pair, a key identifier is

Table 2.1: Number of Loan Transactions and Unique Firms

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
[-0.25cm] Number of Loan Transactions	383.8	490.1	584.7	785.8	975.3	1158.6	1513	1701.6	1988.9	2241.4
Number of Unique Firms	295.2	346.9	425.4	570.7	700.4	814.6	1064.3	1179.4	1402.3	1556.3
Panel A. Number of loan transactions by bank asset size groups										
[-0.25cm] Large Banks	247.9	317.4	332.2	464.1	597.9	734.3	938.2	1022.9	1198.4	1401.2
Mid-sized Sized Banks	118.5	154.6	231.1	297.1	343.2	380.6	519.2	618.3	738.3	792.0
Small Banks	17.4	18.1	20.3	24.7	34.1	43.7	55.6	59.4	52.2	48.3
Panel B. Number of loan transactions by bank business groups										
[-0.25cm] State-owned Banks	124.1	157.0	175.7	266.3	367.0	404.1	526.2	636.3	788.3	907.4
Private Domestic Banks	163.6	206.1	204.7	259.5	325.4	436.6	530.5	520.6	441.6	518.3
Foreign-owned Banks	94.2	125.3	201.6	208.8	225.5	255.7	379.9	463.5	679.8	744.1
Investment & Development Banks	1.9	1.8	1.7	1.5	1.6	2.0	2.6	3.4	4.4	5.3
Participation Banks	-	-	-	49.8	55.9	60.2	73.8	76.9	74.8	66.3

Notes: Table shows the number of commercial loan transactions, aggregated in bank-firm pairs, by banks in Türkiye as of calendar year-ends. Number of unique firms is the total number of firms borrowing from banks. Panel A shows the frequencies by bank-size. We classify banks as follows: Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks. Panel B document the frequencies by bank-business groups. Banks are grouped into 5 classes: State-owned commercial banks (state-owned banks), private domestic commercial banks (private domestic banks), foreign-owned commercial banks (foreign-owned banks), investment and development banks and Participation banks (Islamic banking institutions). The data about participation banks starts in 2010. *Source:* Central Bank of the Republic of Türkiye (CBRT) and The Banking Regulatory and Supervisory Agency (BRSA).

created. Then, all principal amounts of the loans and guarantees for them are aggregated with the same key identifier. Since this data is stock data of loans, it comprises all active loans. Thus, as of December 2016, there are more than 2 million commercial loan observations that belong to more than 1.5 million firms which are used in the loan-network of the banks in Türkiye.

Second, bank-specific control variables were also obtained from CBRT and BRSA databases, which contain information on the balance sheet and income statement of banks. Third, we use Turkish Statistical Institute, Bloomberg, and CBRT databases for macroeconomic data. Definitions and the sources of the list of variables used in the analyses are presented in Table 2.A2 at the end of the chapter.

2.2.2 Construction of Banks' Loan Network

In this section we explain how we construct a network from the common borrower firms. Taking into account the divergence between the share of the common borrowers in terms of their frequency and of the volume of their borrowings presented in Figure 2.1, we construct the bank-network based on two degree measures. Apart from the standard degree measure, which is based on the number of relations, we introduce a new degree centrality measure based on the volume of loans arising from lending to the common firms. In the following subsection, we first summarize in a simple network framework how to create the “projected” inter-bank network from “the bipartite” bank-firm network by using standard degree measure. Then we explain how we construct the “projected” inter-bank network alternatively via our new weighted degree measure.

Bipartite and Projected Networks

A network is composed from a set of nodes (vertices) and links (edges)⁵ between them. It is represented by an adjacency matrix (A) such that the element of the matrix a_{ij} shows whether two nodes are connected or not: $a_{ij}=1$ if there is a link between node i and j ; 0 otherwise. If all nodes in a network are similar in that they belong to the same set, the network is called a one-mode network. An interbank loan network is an example of a one-mode network in which each node i represents a bank. If the nodes can be divided into two sets of nodes and the links exist only between the nodes from different sets, then the network is called a bipartite (two-mode) network.

The bipartite network representation in Figure 2.2a shows the links between the nodes in sets I and J such that $I = \{A, B, C\}$ and $J = \{x, y, z, t, k, m, n\}$. A bank-firm loan network is an example of a bipartite network since the links lie only between two different sets of nodes, banks as lenders and firms as borrowers, and it does not include links within the two distinct sets. In the adjacency matrix of a bipartite network represented in Figure 2.2a, rows refer to the nodes in the set of I and the columns show the nodes in the set of J . The element of the adjacency matrix a_{ij} shows whether there is a link between the nodes $i \in I$ and the nodes $j \in J$.

It is possible to extract two different one-mode networks consisting of one set of nodes of a bipartite network. This method is called one-mode reduction and the derived one-mode networks are called projected (affiliation) networks. Affiliation networks consist of at least two sets of vertices, such that affiliations connect vertices from different sets (Wouter et al., 2005). For example, in the bipartite network in Figure 2.2a, there exists a projected network of the nodes $i \in I$ as a

⁵If links are undirected then they are called edges, if they are directed, then they are known as arcs.

result of their links with the same nodes $j \in J$. In the figure, the edge between B and x and the edge between C and x generate an affiliation between B and C as a result of their relationship with the same node x. Similarly, there exists another projected network of the nodes $j \in J$ as a result of their links with the same nodes $i \in I$. For instance, the edge between x and B and the edge between y and B generates an affiliation between x and y. The matrix representing the mathematical view of the projected network is called an affiliation matrix.

An affiliation matrix (M) is obtained by the multiplication of the adjacency matrix of a bipartite network with its transpose ($A^\top$); i.e., $M = [A \times A^\top]$, with setting all diagonals to 0.⁶ The affiliation matrix of the nodes i in the set of I for the bipartite network in Figure 2.2a is represented as a network graph in Figure 2.2b. The element of the affiliation matrix shows the number of links that both the nodes (banks) i and k from the set I have a link with the same node of j from the set J . Thus the degree of the node i of the projected network is calculated as:

$$d_i = \sum_{i \neq k, k=1}^N m_{ik}, \quad i, k \in I \text{ and } N \text{ is the total number of nodes} \quad (2.1)$$

where

$$m_{ik} = \begin{cases} 0 & \text{if } i = k \\ \sum_{j=1}^J a_{ij} \times a_{kj} & \text{if } i \neq k \text{ where } J \text{ is the total number of firms.} \end{cases} \quad (2.2)$$

There are some studies using bipartite networks for investigating the spillover effects or risk exposures emerging from lending to the same firms. For example,

⁶The other affiliation matrix of the nodes j in the set of J for the bipartite network in Figure 2.2a is gathered by $[A \times A^\top]$, with all diagonals set to 0.

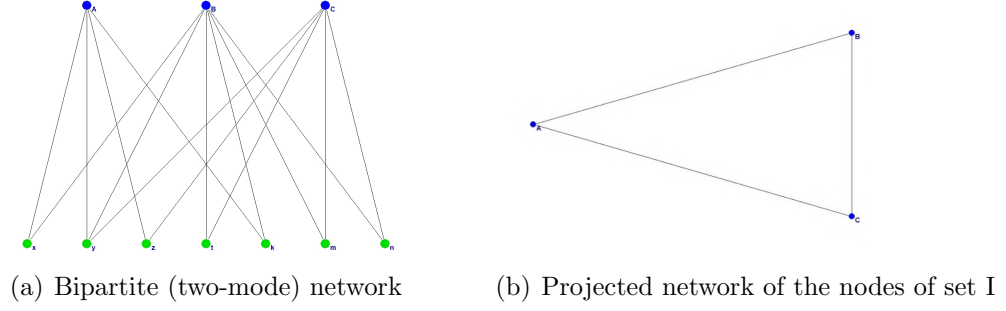


Figure 2.2: Bipartite and Projected Network

Fujiwara et al. (2009) study the impact of exposure of firms to banks and its spillover effects on the banking system in Japan using bipartite network analyses. However, De Masi et al., (2011), De Masi and Gallegati (2012), Lux (2016) and Li et al. (2020) document common exposures to banks caused by their lending to same firms by using projected networks of banks or firms. De Masi et al. (2011) study a bipartite loan network between banks and publicly traded firms in Japan using data for 2004. By employing a Minimal Spanning Tree (MST) method, they identify that there are hubs (the central positions) occupied by the largest banks and argue that the failure of one of those can cause a huge impact in each corresponding subsystem (small regional banks). Similarly, using the MST method, De Masi and Gallegati (2012) present the relations between banks and firms via degree distributions of bipartite loan networks in Italy and In addition, they investigate the structure of the projected bank network gathered from the bipartite loan network. They measure the connectedness in the projected bank network with the degree, i.e. the number of common firms to which banks lend. Fujiwara et al. (2009) investigate loan relationships between commercial banks and publicly traded firms in Japan and present the temporal change in the structure of the bipartite loan network. They develop a fragility score for banks and firms by eigenvalue centrality and identify the nodes with significant fragility scores according to the generated random bipartite graphs.

In this study we first extract the commercial loan network by using degree measure from the projected network analysis as in the literature. In addition to the standard degree of the banks (Equation 2.1), we introduce a new weighted degree centrality measure as explained below (Equation 2.5).

A New Weighted Degree Centrality Measure for Projected Loan Networks

Contrary to the standard degree measure which shows the number of connections between the banks, we introduce a new weighted degree centrality method. This time, the element of the adjacency matrix (A_2), a_{ij} shows the share of the amount of lending that the firm j borrows from bank i within the total amount of loans in the banking sector:

$$a_{ij} = \frac{l_{ij}}{\sum_{j=1}^J \sum_{i=1}^I l_{ij}} \text{ such that } \sum_{i=1}^I \sum_{j=1}^J a_{ij} = 1 \quad (2.3)$$

where l_{ij} is the amount of loan by bank i to firm j and J is the total number of firms and I is the total number of banks.

Then, the element of the affiliation matrix (M_2) of banks, m_{ik} , is calculated as follows:

$$m_{ik} = \begin{cases} 0 & \text{if } i = k \\ \sum_{j=1}^J a_{ij} + a_{kj} & \text{if } a_{ij} \times a_{kj} \neq 0, \text{ where } J \text{ is the total number of firms.} \end{cases} \quad (2.4)$$

The weighted degree centrality of bank i is:

$$wd_i = \sum_{i \neq k, k=1}^I m_{ik}, \text{ where } I \text{ is the total number of banks.} \quad (2.5)$$

Figures 2.3 and 2.4 represent the networks of banks based on their lending to the same firms. The thickness of the edges shows the strength of the connections between the nodes (banks) due to lending to common firms. The networks in Figures 2.3a-2.6a demonstrate the connectedness measured by m_{ik} in (2.4), i.e., via our method. On the other hand, the size of the edges between banks as a measure of connectedness is calculated by m_{ik} in (2.2), i.e., with degree in the networks represented by the figures 2.3b-2.6b. The thickness of the edges in the networks is not comparable between different methods but does indicate the relative degree of the banks within the same network. For instance, while the connectedness between the nodes 1445 and 1972 (Figure 2.3) is relatively high compared to connections among the other banks according to our method (weighted degree measure), it does not seem to be relatively different with respect to the edges among others according to degree measure.

The network figures also show the banks' size and bank-business groupings. The size of the vertices indicates the size group of the banks: large, mid-sized, and small banks.⁷ The color of the vertices shows the groups of the banks according to their business model: state-owned, private domestic, foreign, development and investment, and participation (Islamic) banks. The connectedness between banks increases with the size of banks by both methods. The average centrality is highest in the large banks and lowest in the small banks (Table 2.2, Panel A). On the other hand, weighted degree centrality also differs according to bank's business groups. It is highest in the state-owned banks whereas it is lowest in the development and investment banks (Table 2.2, Panel B).

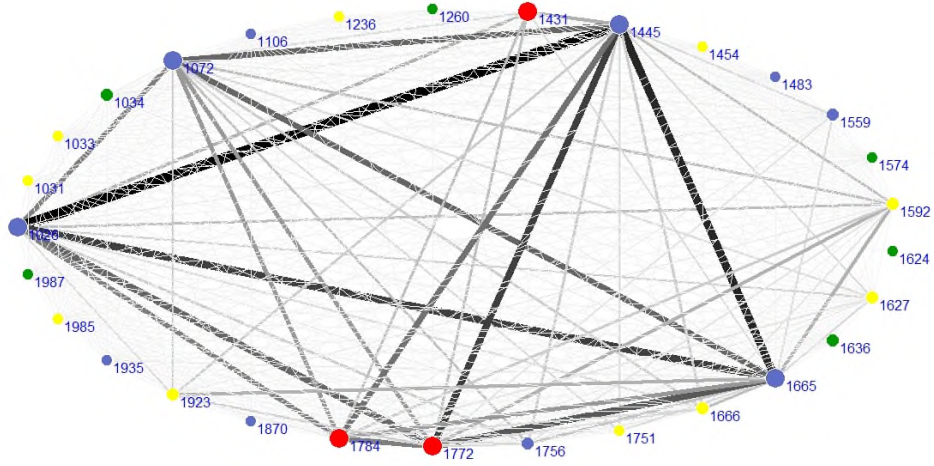
As seen in Table 2.3, the network among banks has increased over time except during 2009 and 2015. This is a result of the fact that the lending share of the

⁷Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks.

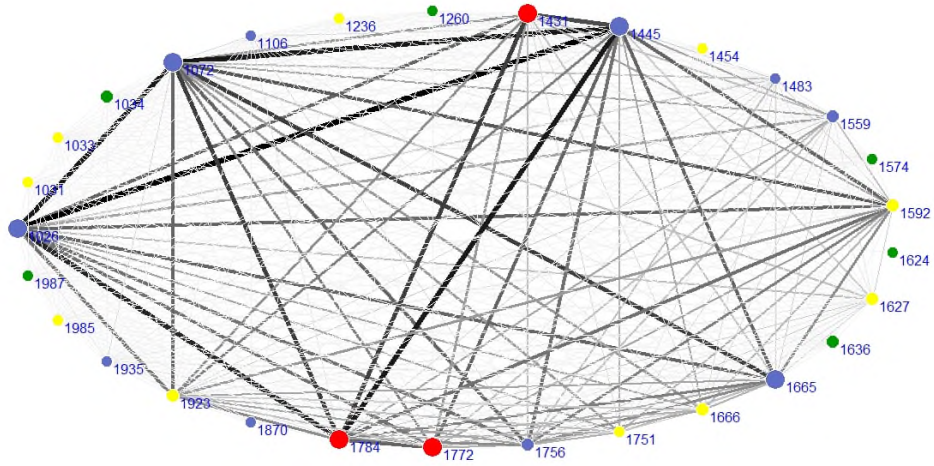
firms borrowing from more than one bank rose over the period between 2007 and 2016 (Figure 2.1). In addition, the number of firms in Türkiye over time consistently increased during the examined period (Table 2.1). The impact of the global financial crisis on the bank-loan network is quite clear, especially in 2009 (Figures 2.4a and 2.4b). For example, while the connections between highly centralized banks grow stronger, they weaken among other banks as a result of the crisis. In addition to the crisis year of 2009, degree centrality also decreased in 2015 (Table 2.3, Figure 2.6). This decline reflects decelerated loan growth due to the Central Bank’s cautious monetary policy stance in 2015. Moreover, as in most other emerging economies, external financing conditions deteriorated in Türkiye as a result of the global economic slowdown driven by the Chinese economy and mounting uncertainties over the Fed’s monetary policy actions in 2015.

Network representations indicate that bank size and business groupings may have an impact on the centrality of the banks (Figure 2.3-2.6). While large banks remain as the most centralized banks in the bank-loan network, small banks demonstrate the lowest degree centrality during the sample period. The degree centrality of the small banks is less stable than that of mid-sized and large banks (Table 2.3). The business groupings also has a consistent and significant impact on the degree centrality. We analyze the impact of the banks’ size and business groupings on their centrality by bank clusters which is obtained by the multiplication of the dummy variables indicating their the related bank business and size groupings in Table 2.A1.⁸

⁸We divide banks into tree size-groups: Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks. We grouped banks into five classes based on their business-types: State-owned commercial banks (state-owned banks), private domestic commercial banks (private domestic banks), foreign-owned commercial banks (foreign-owned banks), and investment and development banks.



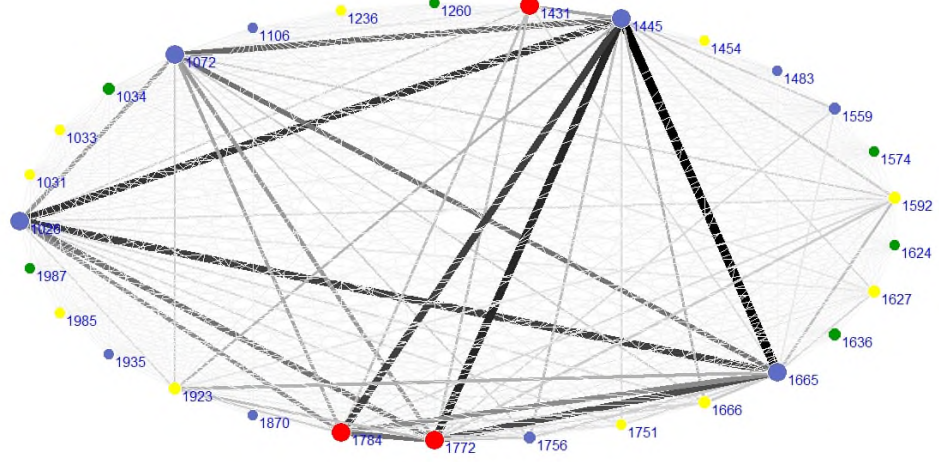
(a) Network by Weighted Degree



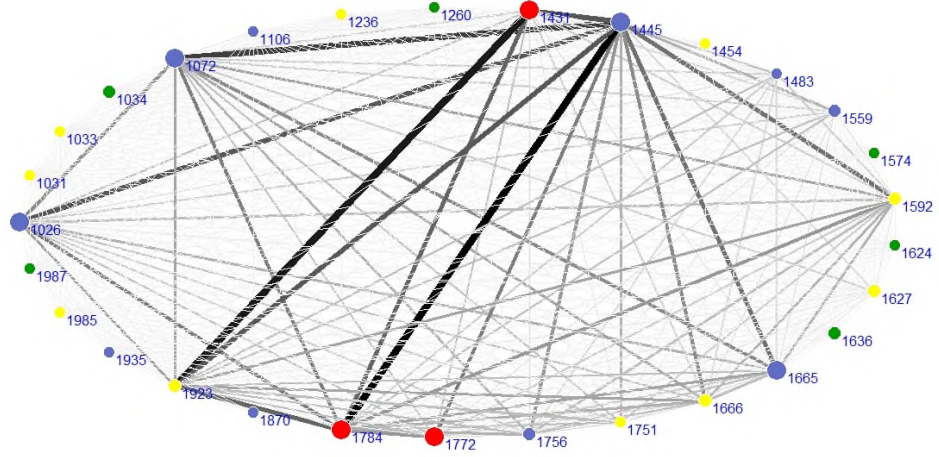
(b) Network by Degree

Figure 2.3: Projected Loan Networks According to Banks' Weighted Degree and Degree Measures as of December 2008.

The figure presents the networks of banks in Türkiye as of December 2008 based on their lending to the same firms. Vertices (nodes) show the banks. The color of the vertices shows the groups of the banks according to their business model; red, blue, yellow, and green demonstrate state-owned, private domestic, foreign, and development and investment banks, respectively. Since the data about participation (Islamic) banks starts in 2010, we have only four business group before then. The size of the vertices indicates the size group of the banks: large, mid-sized, and small banks. The thickness of the edges between the vertices shows the strength of the connections between the nodes (banks) due to lending to common firms. The figure above (a) demonstrates the connectedness measured by our method; weighted degree, while the figure below (b) shows the connectedness measured by degree. The thickness of the edges in the networks is not comparable between different methods but does indicate the relative degree of the banks within the same network. The figures are drawn by Pajek.



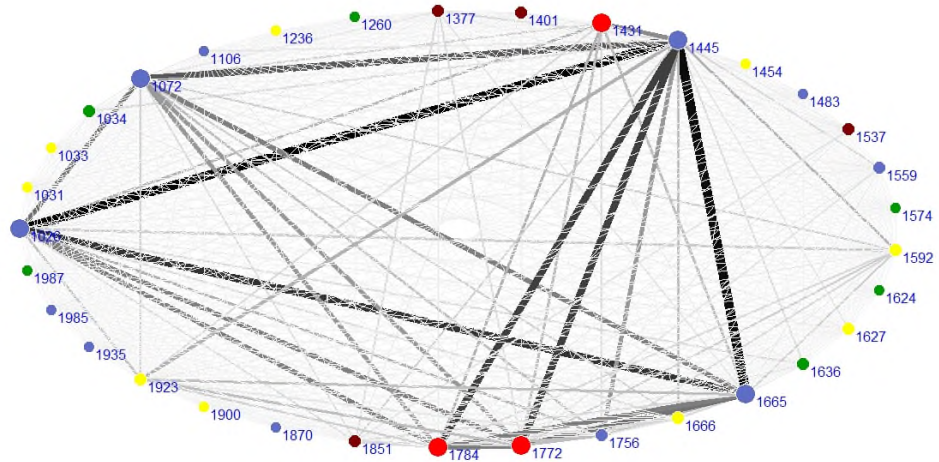
(a) Network by Weighted Degree



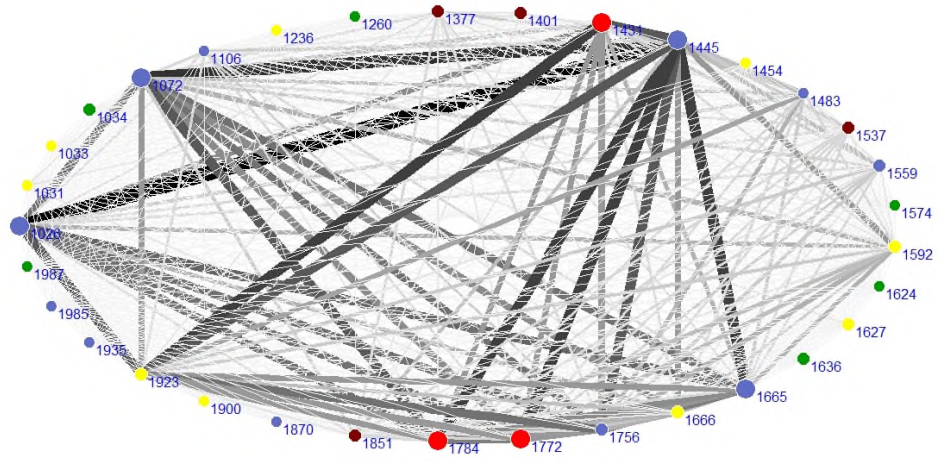
(b) Network by Degree

Figure 2.4: Projected Loan Networks According to Banks' Weighted Degree and Degree Measures as of December 2009.

The figure presents the networks of banks in Türkiye as of December 2009 based on their lending to the same firms. Vertices (nodes) show the banks. The color of the vertices shows the groups of the banks according to their business model; red, blue, yellow, and green demonstrate state-owned, private domestic, foreign, and development and investment banks, respectively. Since the data about participation (Islamic) banks starts in 2010, we have only four business group before then. The size of the vertices indicates the size group of the banks: large, mid-sized, and small banks. The thickness of the edges between the vertices shows the strength of the connections between the nodes (banks) due to lending to common firms. The figure above (a) demonstrates the connectedness measured by our method; weighted degree, while the figure below (b) shows the connectedness measured by degree. The thickness of the edges in the networks is not comparable between different methods but does indicate the relative degree of the banks within the same network. The figures are drawn by Pajek.



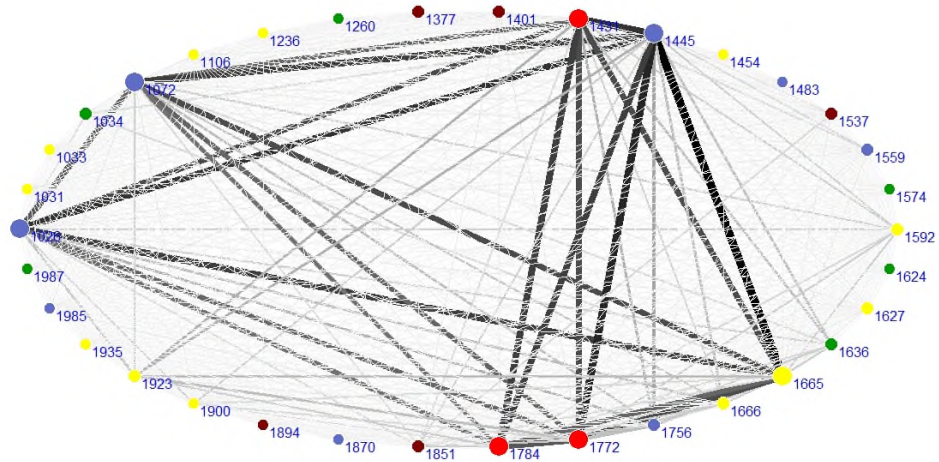
(a) Network by Weighted Degree



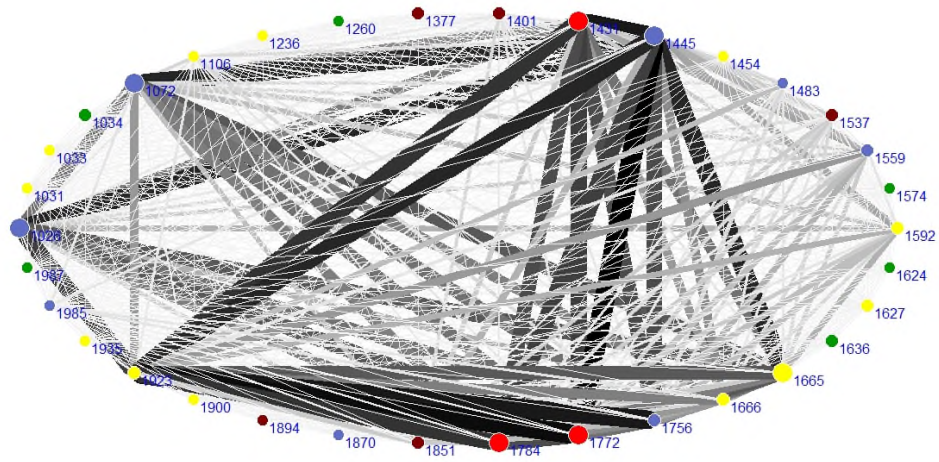
(b) Network by Degree

Figure 2.5: Projected Loan Networks According to Banks' Weighted Degree and Degree Measures as of December 2012.

The figure presents the networks of banks in Türkiye as of December 2012 based on their lending to the same firms. Vertices (nodes) show the banks. The color of the vertices shows the groups of the banks according to their business model; red, blue, yellow, green, and purple demonstrate state-owned, private domestic, foreign, development and investment, and participation banks, respectively. The size of the vertices indicates the size group of the banks: large, mid-sized, and small banks. The thickness of the edges between the vertices shows the strength of the connections between the nodes (banks) due to lending to common firms. The figure above (a) demonstrates the connectedness measured by our method; weighted degree, while the figure below (b) shows the connectedness by degree. The thickness of the edges in the networks is not comparable between different methods but does indicate the relative degree of the banks within the same network. The figures are drawn by Pajek.



(a) Network by Weighted Degree



(b) Network by Degree

Figure 2.6: Projected Loan Networks According to Banks' Weighted Degree and Degree Measures as of December 2015.

The figure presents the networks of banks in Türkiye as of December 2015 based on their lending to the same firms. Vertices (nodes) show the banks. The color of the vertices shows the groups of the banks according to their business model; red, blue, yellow, green, and purple demonstrate state-owned, private domestic, foreign, development and investment, and participation banks, respectively. The size of the vertices indicates the size group of the banks: large, mid-sized, and small banks. The thickness of the edges between the vertices shows the strength of the connections between the nodes (banks) due to lending to common firms. The figure above (a) demonstrates the connectedness measured by our method; weighted degree, while the figure below (b) shows the connectedness by degree. The thickness of the edges in the networks is not comparable between different methods but does indicate the relative degree of the banks within the same network. The figures are drawn by Pajek.

We observe that mid-sized private and foreign banks' degree centrality is significantly higher than mid-sized investment and development banks across the period. During the sample period, there is one large and one small private bank where the ownership status changed, and the degree of those banks increased significantly with the transition from being private domestic to foreign-owned. Interestingly, one mid-size foreign-owned bank's degree also increased significantly after being acquired by another foreign bank, i.e., without any change in the ownership category. These developments imply that the bank acquisitions may affect the banks' penetrations, and hence banks' loan degree centrality.

2.3. Empirical Analysis

The loan network of banks is a derived network across banks and it emerges from having common borrowing firms. The literature identifies the advantages of firms with multiple relationship lenders and banks with common borrowers. For the firms, borrowing from more than one bank is advantageous since it enables them to diversify the risk of premature liquidations and to mitigate hold-up problems (Detragiache et al., 2000; Rajan, 1992). From the lender's point of view, it might be advantageous to have common borrowers for diversifying firm-specific credit risk (Detragiache et al., 2000). Carletti et al. (2007) emphasize that even though multiple-bank lending involves free-riding and duplication of effort, the benefit of greater diversification may dominate the drawbacks of free-riding and duplication of effort, and multiple-bank lending leads to higher per-project monitoring than individual-bank lending.

In this chapter, we focus on the lenders' point of view. Specifically, we investigate whether the connectedness of banks via common borrower firms has a decreasing impact on their loan portfolio riskiness. We use a panel data model to estimate how banks' centrality affects the overall portfolio riskiness of banks. Our sample

covers the period between 2007 and 2016 in a quarterly frequency. Since the variables used in regressions are stationary and the time dimension of the data is relatively higher than the cross-sectional dimension, we employ ordinary least square (OLS) estimation with bank fixed effects (see Table 2.A5 for unit root test results). The fixed effects model assumes that c_i is unobserved time-invariant individual specific and allowed to be correlated with the other explanatory variables. To investigate the association between the credit riskiness and weighted degree centrality, we estimate the following model:

$$Y_{it} = \alpha + \beta \text{ degree}_{it} + \Theta X_{it} + \Psi Z_t + c_i + \epsilon_{it} \quad (2.6)$$

where Y_{it} is the non-performing loan ratio (*npl*) of bank i at time t as a measure of credit riskiness and degree_{it} shows the weighted degree centrality of bank i at time t . We measure the centrality of the banks with our new weighted degree (equation 5). X_{it} is a matrix of the bank-specific characteristics and Z_t indicates a vector of macroeconomic variables. α is the intercept term, β is the coefficient for weighted degree centrality, c_i is the unobserved bank-specific fixed effects and ϵ_{it} is the idiosyncratic error term following i.i.d. process with zero mean and variance σ_ϵ^2 . Bank-specific controls, X_{it} , are the overall granted loan volume of the banks, banks' profitability, liquidity, efficiency, and capital. The overall granted loan volume of the banks is measured by the natural logarithm of a bank's total loans, $\ln(\text{loans})$. Banks' profitability, liquidity, and efficiency are proxied by (*roa*) (the return over total assets ratio), *liquid asset* (the ratio of liquid assets over total assets), and *non-interest expenses* (the ratio of non-interest expenses over total assets). Capital, *coa*, is the ratio of equity over total assets. Macroeconomic control variables, Z_t , are the sovereign risk proxied by the 5-year credit default swap

Table 2.2: Summary Statistics of Weighted Degree Measures Across Banks

Panel A. Bank Size Group	Observation	Mean	Standard Deviation	Minimum	25th	Percentile 50th	75th	Maximum
Large Banks	280	58.870	20.798	5.616	6.519	63.009	92.422	95.741
Mid-sized Banks	320	20.965	9.075	1.855	14.028	19.910	28.221	39.972
Small Banks	520	5.057	4.513	0.018	1.287	3.222	8.489	16.440
Panel B. Bank Business Groups								
State-owned Banks	120	49.989	20.095	5.616	31.312	58.188	63.756	77.475
Private Banks	394	33.519	29.161	0.064	9.520	18.523	63.876	95.741
Foreign Banks	366	14.879	12.866	0.043	4.686	12.224	25.529	75.021
Investment and Development Banks	240	4.878	6.435	0.018	1.022	1.825	6.792	27.785

Notes: Table shows the summary statistics the weighted degree measure of banks during the sample period between March 2007 and December 2016. Weighted degree measure shows the connectivity among banks resulted from their common borrower firms. Panel A shows the statistics by banks' sizes groups. We classify banks as follows: Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks. Panel B documents the summary statistics of weighted degree measure of banks by their business groups. We grouped banks into 5 classes based on their business-types: State-owned commercial banks (state-owned banks), private domestic commercial banks (private domestic banks), foreign-owned commercial banks (foreign-owned banks), investment and development banks and participation banks (Islamic banking institutions). The data about participation banks starts in 2010. We use their information for calculating the network at each related period, if the data is available. On the other hand, we exclude them from the regression analysis as the remaining sample allows us to have a balanced panel covering more than 88 percent of assets in the banking sector as of December 2016. *Source:* Central Bank of the Republic of Türkiye and The Banking Regulatory and Supervisory Agency.

Table 2.3: Weighted Degree Measures by Banks' Size Groups

Year	Bank Size Groups		
	Large Banks	Mid-Sized Banks	Small Banks
2007	26.872	16.065	3.646
2008	56.410	23.767	4.368
2009	54.867	22.300	5.114
2010	58.234	23.299	5.172
2011	61.184	25.730	6.779
2012	64.172	26.012	7.716
2013	67.767	26.415	8.169
2014	72.857	27.154	8.070
2015	71.625	24.822	7.564
2016	73.517	21.399	7.498

Notes: Table shows the average of the weighted degree measure of banks across their size as of the end of the year during the sample period between 2007 and 2016. Weighted degree measure shows the connectivity among banks resulting from their common borrower firms capturing the impact of the volume of their loans. Large banks have assets of more than five percent of the banking sector assets, while medium banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks.

premium for Türkiye (*cds*), economic growth measured as the two-period lag of real GDP growth (*gdp growth*), and monetary policy stance proxied by the weighted average cost of funding of the CBRT (*aofm*). Summary statistics of the variables used in the baseline model are represented in Table 2.4.

We also inquiry whether the size of the loan transactions in a banks' portfolio has an impact on the relation between the portfolio riskiness and banks' centrality. There exist a number of studies addressing the relation between firm size and firm riskiness. Jiménez and Saurina (2004), Bunn and Redwood (2003) show that smaller firms are more likely to default. Belaid et al. (2017) and Bonfim (2009), on the other hand, find no relation between firm size and probability of credit default. Based on this evidence, we assume that the loan size may have an impact on a bank's overall credit riskiness as a result of the fact that small firms are opaque and

generally borrow smaller amounts while large firms are transparent and borrow higher amounts. In order to disentangle the impact of loan size on bank credit risk, we stratified the loan-level data into four sub-samples according to the size of the individual commercial loans by banks. The boundaries of the strata are determined by SMEs' asset size boundaries and their average borrowings from banks. Therefore, the inflationary impacts on the limits of the strata are also taken into account. From each sub-sample, we extract the bank-loan network and compute the weighted degree centrality of the banks. In addition, we calculate the non-performing loan ratio of the banks for each strata separately. Finally, we estimate our baseline model for each of these four sub-samples separately. Dependent variables are npl_LS1 to npl_LS4 , indicating the non-performing loan ratio of the banks for commercial loans that is stratified on their size. The first sample $LS1$ includes the loans with the lowest amounts and the last sample $LS4$ covers the loans with the highest amounts in each period across the banks. $degree_LS1$ to $degree_LS4$ show the weighted degree centrality of banks originating from the bank-loan network of the related loan-size sub-samples; i.e., $LS1$ to $LS4$. The first sub-sample ($LS1$) includes the loans with the lowest amounts whereas the last sub-sample ($LS4$) covers the loans with the highest amounts in each period across the banks. Summary statistics and Pearson's Correlations of the variables are shown in Table 2.A3 and Table 2.A4 at the end of the chapter, respectively.

Table 2.5 presents the estimation results with fixed effects and random effects methods. All of the estimations indicate that there is a negative and significant association between the loan-centrality of banks and their credit riskiness, and this relation is robust to loan-size groups. Moreover, we observe that the coefficient of the weighted degree centrality is consistently decreasing across the sub-samples

Table 2.4: Summary Statistics of the Variables Used in the Baseline Model

Variables	Standard		Percentile				
	Mean	Deviation	Minimum	25th	50th	75th	Maximum
<i>degree</i>	27.856	25.745	0.043	7.996	17.584	46.598	95.741
<i>npl</i>	3.630	1.944	0.061	2.201	3.320	4.942	11.680
<i>ln(loans)</i>	16.109	1.825	10.166	14.728	16.282	17.611	19.241
<i>eea</i>	13.123	7.139	5.730	10.013	11.627	13.654	95.337
<i>roa</i>	8.634	6.601	-19.340	4.721	8.624	12.849	50.332
<i>liquid asset</i>	26.952	12.966	5.252	18.335	23.763	32.565	75.365
<i>non-interest expenses</i>	32.028	10.761	13.227	23.434	30.021	37.947	82.727
<i>cds</i>	225.112	66.170	127.026	174.343	215.391	268.646	408.688
<i>gdp growth</i>	4.880	5.166	-14.541	3.324	5.530	8.312	11.802
<i>aofm</i>	9.575	3.846	5.110	7.110	8.550	10.011	18.062

Notes: The table shows the summary statistics of the bank panel during the sample period between March 2007 and December 2016. The number of observation is 880. The $degree_{it}$ is the network centrality of the Turkish banks, measured by weighted degree, originating from their lending to common firms. Bank controls are the following: $ln(loans)$ is the natural logarithm of a bank's total loans, roa is the return over total assets ratio, eea is the ratio of equity over total assets for each bank, $liquid assets$ is the ratio of liquid assets over total assets as a proxy for a bank's liquidity, $non-interest expenses$ is the ratio of non-interest expenses over total assets. Macroeconomic control variables are cds is the 5-year credit default swap premium for Türkiye, $gdp growth$ is the two-period lag of real GDP growth, $aofm$ is the weighted average cost of funding of the Central Bank of the Republic of Türkiye.

from the one with the lowest loan volume toward the highest. This result implies that the impact of loan centrality on banks' credit riskiness is higher for the smaller loans.

In Table 2.6, we present that the size of the loan portfolio has a significantly positive impact on credit riskiness for samples with larger loans (*LS3* and *LS4*), while its impact is insignificant for samples with smaller loans (*LS1* and *LS2*). This can be attributed to the high correlations between the size of the loan portfolio and our weighted degree for larger loans (Table 2.A4 at the of the chapter). Liquidity seems to have a significantly increasing impact on credit riskiness. However, this is because the increase in liquidity causes less lending and has an increasing effect on the ratio of non-performing loans. The non-interest expenses have a significantly positive impact on credit riskiness for all loan size groups except the *LS1*. The difference in the significance of the impact between samples with the smaller and the larger loan volumes can be explained by the previous evidence that small firms are opaque and generally borrow smaller amounts compared to large firms that are transparent and generally borrow higher amounts, and the impact of inefficiency on the credit riskiness is higher for the larger loan size groups. GDP growth has a significantly decreasing impact on large loan groups as a result of the fact that this group of loans is related to investments. There is a negative relation between the monetary policy stance and bank credit riskiness, indicating the presence of the risk-taking channel.

2.3.1 Additional Results and Robustness Tests

As we described in detail in Section 2.2.2, loan centrality emerges from banks lending to the same firms. In the absence of firms' borrowing from multiple banks,

there will be no loan centrality. One may argue that loan centrality might be capturing only the impact of multiple borrowing. However, we argue that loan centrality is more than firms' multiple borrowing because it takes into account all bilateral lending transactions to the same firms, and exploit this information in explaining the differences in banks' portfolio risk management. Thus, we add two proxies to our baseline model: number of common borrowing firms to other borrowing firms in (*common firms1*) and the ratio of loans of the common borrowing firms to loans of other borrowing firms within each bank (*common firms2*), and control for the impact of multiple borrowing firms on the credit riskiness of banks. As seen in Table 2.7 and Table 2.8, the impact of loan centrality remains significant for the whole sample as well as all of the sub-samples. These findings suggest that the negative and significant association between loan centrality and bank's loan portfolio riskiness that we document is not driven by the multiple borrowing relationships.

The unit of observation in our analyses until now is the bank-quarter and the regression results presented in Table 5-8 shows the association between bank's loan portfolio riskiness and centrality on a bank-basis. It can be argued that these findings suggest that the highly centralized banks grant their loans to the less-risky firms. Hence, to query this argument and reduce the possibility of introducing data aggregation bias in the previous analysis, following Jiménez and Saurina (2004) we estimate a binomial logit model by utilizing loan-level data:

$$Prob(y_{jt} = 1|X_{jt}, Z_{it}, P_{kt}, v_{jt}) = \frac{1}{(1 + \exp(\Theta X_{jt} + \Gamma Z_{it} + \Psi P_{kt} + v_{jt}))} \quad (2.7)$$

where $Prob(y_{jt} = 1|X_{jt}, Z_{it}, P_{kt}, v_{jt})$ is the probability of default of the loan j and t , i , k indicate time periods (quarters), banks, and firms, respectively, and v_{jt} is i.i.d. with $N(0, \sigma_v^2)$. X_{jt} is the matrix of loan characteristics such as loan size dummies

and loan collateral dummy.

We define a loan as a defaulted loan if it becomes a non-performing loan. In Türkiye, loans are classified in five groups according to Code of Provisions: Loans of a Standard Nature (Group I), Loans Under Close Monitoring (Group II), Loans with Limited Collectability (Group III), Doubtful Loans (Group IV) and Loans classified as Loss (Group V). Loans from the first and second classifications called as performing loans and the remaining ones called as non-performing loans.

Similarly we refer a loan as a defaulted loan if it is classified under the group of III, IV or V. In other words, a defaulted loan is a loan if it past due principal and/or interest payments more than 90 days.

Loans are stratified into four sub-samples as it is done in the previous analyses. There are 4 loan size dummies; *Micro-Sized Loans*, *Small-Sized Loans*, *Mid-Sized Loans*, *Large-Sized Loans* indicating whether the loan belongs to the related size-grouping and the constant includes the impacts of Micro-Sized Loans. The boundaries of the size-stratus are determined by SMEs' asset size boundaries and their average borrowings from banks. *Small-Sized Loans*, *Mid-Sized Loans*, and *Large-Sized Loans* are dummy variables, taking on a value of one if a loan is grouped into the small-sized loans, mid-sized loans, or large-sized loans, respectively, or zero otherwise. *Collateral* dummy variable shows whether there is a collateral covering the entire amount of the loan granted.

Z_{it} is the matrix of bank characteristics representing banks' connectedness grouping dummies. We divide banks into three groups: strongly connected, moderately connected, and weakly connected banks. For each time t (quarter), we calculate the weighted degree of the banks, then grouped them according to the following: The banks with a lower than mean degree of all banks in the related quarter placed in the weakly connected bank group. The remaining banks are

divided into two: banks with a lower than mean degree are placed in the moderately connected bank group, and the others are classified in the strongly connected bank group. Hence, *Strongly Connected Banks*, *Moderately Connected Banks*, and *Weakly Connected Banks* dummies indicate whether the loan belongs to the related connectedness-grouping and the constant includes the impacts of weakly connected banks. P_{kt} shows the vector of firm characteristic dummy indicating whether a firm borrows from more than one bank. it takes on a value of one if the firm borrows from at least 2 banks, zero otherwise.

The estimates of the parameters have been obtained by maximizing the log likelihood function of y_{jt} . Underlying this model is the variance components model that y_{jt} is related to another latent non-observable random variable y_{jt}^* which takes the form

$$y_{jt}^* = \Theta X_{jt} + \Gamma Z_{it} + \Psi P_{kt} + v_{jt} + \epsilon_{jt} \quad (2.8)$$

where $-\epsilon_{jt}$ is conditional upon X_{jt}, Z_{it}, P_{kt} follows a logistic distribution and the relation between y_{jt} and y_{jt}^* is as follows: if $y_{jt}=1$ then $y_{jt}^* > 0$; zero otherwise.

We estimate a logit model using loans granted by 22 banks during the period of 2007Q1 through 2016Q4. We have more than 42 million observations belonging to about five million loan transactions of more than three million firms. As explained above, all the variables used in the panel-logit estimations are dummy variables which take values of zero or one. Our loan-level panel logit regression results show that the probability of default decreases with loan size and (Table 2.9). Having as much collateral as the loan itself reduces the probability of default. In addition, loan-level analysis indicates that the odds of being defaulted is higher if a firm borrows more than one bank.

Finally, our loan-level evidence shows that the probability of default is higher in banks with higher centrality compared to weakly connected banks. On the other

hand, our bank-level estimation results presented in Table 2.5 to Table 2.8 show that overall portfolio riskiness of banks decrease with the centrality of the banks. Based on these evidence from the loan-level and aggregated bank-level data, our results imply that highly centralized banks manage their loan portfolios better.

2.4. Conclusion

In this chapter, we focus on bank connectedness that results from common firms' borrowings. Though the share of firms borrowing from multiple banks is very low, the amount of loans borrowed by these corporations has been in the range of 75-80 percent of the total loans granted by the whole banking system in Türkiye during the sample period of 2007-2016. In this setting, we first construct a bank loan network originated by bank-firm commonality structure and develop a new weighted degree centrality measure based on the share of the loans that banks lend to the same firms. Then we conduct an empirical analysis to investigate the impact of banks' connectedness on banks' overall portfolio riskiness.

Our network analysis presents that the projected loan network topology with different degree measurements diverge significantly from each other, and we argue that our weighted degree centrality represents the connectedness better given the multiple banking structure. Using our connectedness measure, we empirically show that there is a significant negative association between banks' portfolio riskiness and their degree of connectedness. The impact of degree centrality on credit riskiness remains significant after controlling for the size of the loan portfolio and the liquidity of the banks and even after controlling for multiple borrowing of the banks. In addition, the negative association becomes more evident in smaller loan size groups. Analysis based on the transaction-level regressions indicating that probability of default is higher in banks with higher centrality compared to weakly

connected banks reveals that highly centralized banks are able to manage their overall portfolio riskiness better.

Our findings suggest that banks may have an incentive to increase their centrality to exploit the benefits of having overlapping loan portfolios. While it is advantageous for banks to increase their connectedness, it may be disadvantageous for the banking system, i.e., increase contagion (Lux, 2016; Biswas and Gómez, 2018; Liu et al., 2020). Therefore, there may be a contradiction in terms of bank's lending behaviour and the stability of the system when the connectedness of banks is rooted in common borrowers. The policy implication of our study is that the projected networks based on common borrowers of banks will be a practical use for bank supervisors and central banks to monitor banks and to measure the net benefits of the negative and positive externalities of an interconnected financial system to ensure financial stability.

Table 2.5: Estimation Results of the Baseline Model

	<i>npl</i> (<i>fixed</i>)	<i>npl</i> (<i>random</i>)
<i>degree</i>	-0.049 *** (0.006)	-0.047 *** (0.006)
Bank Characteristics (X_{it})		
<i>ln(loans)</i>	0.405 ** (0.176)	0.407 *** (0.144)
<i>roa</i>	-0.016 (0.012)	-0.016 (0.012)
<i>eoaa</i>	0.023 (0.014)	0.021 (0.014)
<i>liquid asset</i>	0.068 *** (0.009)	0.068 *** (0.007)
<i>non-interest expenses</i>	0.059 *** (0.009)	0.059 *** (0.009)
Macroeconomic Control Variables (Z_t)		
<i>cds</i>	-0.000 (0.001)	-0.000 (0.001)
<i>gdp growth</i>	-0.067 *** (0.012)	-0.067 *** (0.012)
<i>aofm</i>	-0.183 *** (0.0190)	-0.178 *** (0.0177)
<i>Constant</i>	-3.361 (3.300)	-3.482 (2.653)
Number of observations	860	860
Number of banks	22	22
R-squared	0.311	0.3107
F-stat	41.54 ***	
Wald Chi-Squared		369.63 ***
Hausman Test: χ^2	9.19	

Notes: The table reports the ordinary least squares regressions results. Analysis covers the period of 2007–2016 in a quarterly frequency. The dependent variable is (*npl*), the non-performing ratio of the commercial loans by Turkish banks. *degree_{it}* is the network centrality of the Turkish banks, measured by weighted degree, originating from their lending to common firms. Bank controls are the following: *ln(loans)* is the natural logarithm of a bank's total loans, *roa* is the return over total assets ratio, *eoaa* is the ratio of equity over total assets for each bank, *liquid assets* is the ratio of liquid assets over total assets as a proxy for a bank's liquidity, *non-interest expenses* is the ratio of non-interest expenses over total assets. Macroeconomic control variables are: *cds* is the 5-year credit default swap premium for Türkiye, *gdp growth* is the two-period lag of real GDP growth, *aofm* is the weighted average cost of funding of the Central Bank of Türkiye. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels, ***, **, * indicating the significance level at $p=0.01$, 0.05 , and 0.1 , respectively, are placed adjacently. Details of the variables are described in Table 2.A2 at the end of the chapter.

Table 2.6: Estimation Results by Loan Size Groups

Variables	<i>npl_LS1</i> (<i>fixed</i>)	<i>npl_LS1</i> (<i>random</i>)	<i>npl_LS2</i> (<i>fixed</i>)	<i>npl_LS2</i> (<i>random</i>)	<i>npl_LS3</i> (<i>fixed</i>)	<i>npl_LS3</i> (<i>random</i>)	<i>npl_LS4</i> (<i>fixed</i>)	<i>npl_LS4</i> (<i>random</i>)
<i>degree_LS1</i>	-0.853*** (0.240)	-0.947*** (0.218)						
<i>degree_LS2</i>			-0.184*** (0.044)	-0.196*** (0.041)				
<i>degree_LS3</i>					-0.104*** (0.012)	0.119*** (0.011)		
<i>degree_LS4</i>							-0.019*** (0.003)	-0.017*** (0.003)
Bank Characteristics (X_{it})								
<i>ln(loans)</i>	-1.240 (1.325)	0.444 (0.812)	1.169 (0.829)	0.622 (0.571)	4.095*** (0.516)	1.790*** (0.339)	0.333 (0.202)	0.389*** (0.143)
<i>roa</i>	-0.561*** (0.094)	-0.573*** (0.092)	-0.427*** (0.057)	-0.438*** (0.057)	0.117*** (0.035)	0.087*** (0.035)	-0.071*** (0.013)	-0.071*** (0.013)
<i>eoq</i>	-0.838*** (0.207)	-0.492*** (0.187)	0.201*** (0.066)	0.215*** (0.061)	-0.140*** (0.041)	-0.189*** (0.039)	0.026 (0.024)	0.032 (0.022)
<i>liquid asset</i>	0.012 (0.063)	0.074 (0.047)	0.092*** (0.041)	0.071*** (0.034)	0.182*** (0.026)	0.085*** (0.020)	0.056*** (0.011)	0.058*** (0.008)
<i>non-interest expenses</i>	0.053 (0.072)	0.081 (0.063)	0.205*** (0.045)	0.176*** (0.041)	0.131*** (0.028)	0.065*** (0.026)	0.047*** (0.010)	0.046*** (0.009)

Table 2.6. (continued)

Macroeconomic Control Variables (Z_t)									
<i>cds</i>	0.002 (0.007)	0.03 (0.007)	0.008* (0.005)	0.009* (0.005)	0.001 (0.003)	0.003 (0.003)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
<i>gdp growth</i>	-0.116 (0.084)	-0.098 (0.084)	-0.128** (0.058)	-0.134** (0.058)	-0.109*** (0.036)	-0.117*** (0.037)	-0.038*** (0.013)	-0.038*** (0.013)	-0.039*** (0.013)
<i>aofm</i>	-1.036*** (0.129)	-0.934*** (0.118)	-0.653*** (0.0925)	-0.688*** (0.0827)	-0.274*** (0.0575)	-0.420*** (0.0515)	0.0263 (0.0219)	0.0263 (0.0219)	0.0363* (0.0194)
<i>Constant</i>	59.43** (25.53)	24.57 (15.99)	-8.673 (15.81)	1.916 (10.78)	-60.67*** (9.848)	-16.14** (6.279)	-3.577 (3.921)	-3.577 (3.921)	-4.830* (2.707)
Number of observations	829	829	858	858	853	853	811	811	811
Number of banks	22	22	22	22	22	22	22	22	22
R-squared	0.191	0.1877	0.200	0.1987	0.291	0.2713	0.228	0.228	0.2278
F-stat	20.92***		22.92***		37.44***		25.63***		
Wald Chi-Squared		178.37***		221.43***		284.1***		224.22***	
Hausman Test: χ^2	26.45***		13.17		50.55***		11.49		

Notes: The table reports the ordinary least squares regressions results. The loan-level data is stratified into four sub-samples according to the size of the individual commercial loans by banks. Dependent variables are *npl_L51* to *npl_LS4*, indicating the non-performing loan ratio of the banks for commercial loans which is stratified on their size. The first sample *LS1* includes the loans with the lowest amounts, the last sample *LS4* covers the loans with the highest amounts in each period across the banks. The boundaries of the strata are determined by SMEs' asset size boundaries and their average borrowings from banks. *degree_LS1* to *degree_LS4* show the weighted degree centrality of banks originating from the bank-loan network of the related loan-size sub-samples; i.e., *LS1* to *LS4*. Bank controls are the following: *ln(loans)* is the natural logarithm of a bank's total loans, *roa* is the return over total assets ratio, *boa* is the ratio of equity over total assets for each bank, *liquid assets* is the ratio of liquid assets over total assets as a proxy for a bank's liquidity, *non-interest expenses* is the ratio of non-interest expenses over total assets. Macroeconomic control variables are: *cds* is the 5-year credit default swap premium for Türkiye, *gdp growth* is the two-period lag of real GDP growth, *aofm* is the weighted average cost of funding of the Central Bank of the Republic of Türkiye. Analysis covers the period of 2007–2016 in a quarterly frequency. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels, ***, **, * indicating the significance level at $p=0.01$, 0.05, and 0.1, respectively, are placed adjacently. Details of the variables are described in Table 2.A2 at the end of the chapter.

Table 2.7: Estimation Results of the Baseline Model Controlling for Multiple Borrowing

	<i>npl</i> (<i>fixed</i>)	<i>npl</i> (<i>fixed</i>)
<i>degree</i>	-0.050*** (0.007)	-0.048*** (0.007)
Bank Characteristics (X_{it})		
<i>common firms1</i>	-0.040 (0.037)	
<i>common firms2</i>		0.027* (0.015)
<i>ln(loans)</i>	0.389** (0.177)	0.358** (0.178)
<i>roa</i>	-0.017 (0.012)	-0.019 (0.012)
<i>eoal</i>	0.025* (0.014)	0.015 (0.015)
<i>liquid assets</i>	0.066*** (0.009)	0.069*** (0.009)
<i>non-interest expenses</i>	0.057*** (0.009)	0.061*** (0.009)
Macroeconomic Control Variables (Z_t)		
<i>cda</i>	-0.000 (0.001)	-0.000 (0.001)
<i>gdp growth</i>	-0.067*** (0.012)	-0.066*** (0.012)
<i>aofm</i>	-0.189*** (0.020)	-0.177*** (0.019)
<i>Constant</i>	-2.800 (3.341)	-2.815 (3.311)
Number of observations	860	860
Number of banks	22	22
R-squared	0.312	0.313
F stat	37.51***	37.78***

Notes: The table reports the ordinary least squares regressions results. Controlling variables additional to the variables in Table 2.5 are: *common firms1*; the ratio of the number of firms borrowing also from other banks to the number of firms borrowing only from the bank itself, and *common firms2*; the ratio calculated by the total amount of the loans that firms borrows also from other banks over the total amount of loans that firms financed only by the bank itself. Analysis covers the period of 2007–2016 in a quarterly frequency. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels, ***, **, * indicating the significance level at $p=0.01$, 0.05 , and 0.1 , respectively, are placed adjacently. Details of the variables are described in Table 2.A2 at the end of the chapter.

Table 2.8: Estimation Results by Loan Size Groups Controlling for Multiple Borrowing

Variables	<i>npl_LS1</i> (fixed)	<i>npl_LS1</i> (fixed)	<i>npl_LS2</i> (fixed)	<i>npl_LS2</i> (fixed)	<i>npl_LS3</i> (fixed)	<i>npl_LS3</i> (fixed)	<i>npl_LS4</i> (fixed)	<i>npl_LS4</i> (fixed)
<i>degree_LS1</i>	-0.807*** (0.243)	-0.754 (0.246)						
<i>degree_LS2</i>			-0.152*** (0.044)	-0.169*** (0.044)				
<i>degree_LS3</i>					-0.114*** (0.012)	-0.106*** (0.012)		
<i>degree_LS4</i>							-0.019*** (0.003)	-0.019*** (0.003)
Bank Characteristics (X_{it})								
<i>common_firms1</i>	0.293 (0.257)		0.838*** (0.176)		-0.466*** (0.112)		-0.034 (0.039)	
<i>common_firms2</i>		0.243* (0.136)		0.206*** (0.073)	-0.065 (0.046)		0.004 (0.021)	
<i>ln(loans)</i>	-1.122 (1.329)	-1.959 (1.383)	1.628** (0.824)	0.840 (0.834)	3.825*** (0.515)	4.198*** (0.521)	0.314 (0.203)	0.321 (0.210)
<i>roa</i>	-0.559*** (0.094)	-0.591*** (0.095)	-0.411*** (0.057)	-0.454*** (0.058)	0.109*** (0.035)	0.125*** (0.036)	-0.071*** (0.013)	-0.071*** (0.013)
<i>eoal</i>	-0.839*** (0.207)	-0.874*** (0.208)	0.174*** (0.065)	0.144** (0.068)	-0.121*** (0.041)	-0.121*** (0.043)	0.027 (0.024)	0.026 (0.024)
<i>liquid assets</i>	0.025 (0.064)	0.003 (0.063)	0.131*** (0.042)	0.099** (0.041)	0.156*** (0.026)	0.179*** (0.026)	0.054*** (0.011)	0.055*** (0.011)
<i>non-interest expenses</i>	0.069 (0.073)	0.062 (0.072)	0.248** (0.045)	0.222*** (0.045)	0.102*** (0.029)	0.125*** (0.028)	0.045*** (0.010)	0.047*** (0.010)

Table 2.8. (continued)

Macroeconomic Control Variables (Z_t)								
cds	0.002 (0.007)	0.002 (0.007)	0.007 (0.005)	0.008* (0.005)	0.002 (0.003)	0.001 (0.003)	-0.005** (0.001)	-0.005*** (0.001)
$gdp\ growth$	-0.113 (0.084)	-0.109 (0.084)	-0.120** (0.057)	-0.124** (0.058)	-0.111*** (0.036)	-0.109*** (0.036)	-0.039*** (0.013)	-0.038*** (0.013)
$aofm$	-0.992*** (0.135)	-0.982*** (0.133)	-0.521*** (0.095)	-0.608*** (0.093)	-0.355*** (0.060)	-0.289*** (0.058)	0.021 (0.023)	0.027 (0.022)
$Constant$	55.42** (25.76)	69.48*** (26.11)	-22.00 (15.85)	-5.006 (15.79)	-52.61*** (9.942)	-61.76*** (9.872)	-3.022 (3.973)	-3.409 (3.998)
Number of observations	829	829	858	858	853	853	811	811
Number of banks	22	22	22	22	22	22	22	22
R-squared (overall)	0.192	0.194	0.221	0.207	0.305	0.292	0.229	0.228
F-stat	18.97***	19.20***	23.43***	21.60***	36.10***	33.94***	23.14***	23.04***

Notes: The table reports the ordinary least squares regressions results. The loan-level data is stratified into four sub-samples according to the size of the individual commercial loans by banks. Dependent variables are *npl_L\$1* to *npl_L\$4* indicating the non-performing loan ratio of the banks for commercial loans which is stratified on their size. The first sample *LS1* includes the loans with the lowest amounts, the last one *LS4* covers the loans with the highest amounts in each period across the banks. The Boundaries of the strata are determined by SME's asset size boundaries and their average borrowings from banks. *degree_L\$1* to *degree_L\$4* show the weighted degree centrality of banks originating from the bank-loan network of the related loan-size sub-samples; i.e., *LS1* to *LS4*. Bank controls are the following: *common_firms1* is the ratio of the number of firms borrowing also from other banks to the number of firms borrowing only from the bank itself, *common_firms2* is the ratio calculated by the total amount of the loans that firms borrows also from other banks over the total amount of loans that firms financed only by the bank itself, *ln(loans)* is the natural logarithm of a bank's total loans, *roa* is the return over total assets ratio, *eo* is the ratio of equity over total assets for each bank, *liquid assets* is the ratio of liquid assets over total assets as a proxy for a bank's liquidity, *non-interest expenses* is the ratio of non-interest expenses over total assets. Macroeconomic control variables are: *cds* is the 5-year credit default swap premium for Türkiye, *gdp growth* is the two-period lag of real GDP growth, *aofm* is the weighted average cost of funding of the Central Bank of the Republic of Türkiye. Analysis covers the period of 2007–2016 in a quarterly frequency. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels, ***, **, *, indicating the significance level at p=0.01, 0.05, and 0.1, respectively, are placed adjacently. Details of the variables are described in Table 2.A2 at the end of the chapter.

Table 2.9: Estimation Results for the Probability of Default of Loans Borrowed by Firms

Loan Characteristics (X_{jt})		
Small-Sized Loans (=1, otherwise 0)	-1.603*** (0.005)	-1.946 *** (0.005)
Mid-sized Loans (=1, otherwise 0)	-2.835*** (0.008)	-3.257 *** (0.009)
Large-Sized Loans (=1, otherwise 0)	-3.442*** (0.017)	-3.908 *** (0.017)
Collateral (=1; if Collateral>=Loan, otherwise 0)	-3.764*** (0.004)	-3.757 *** (0.004)
Firm Characteristics (P_{kt})		
Multiple Borrowing (=1; if a firm borrows from at least 2 banks at t, otherwise 0)		0.824 *** (0.004)
Bank Characteristics (Z_{it})		
Moderately Connected Banks (=1, otherwise 0)	0.779*** (0.017)	0.918 *** (0.017)
Strongly Connected Banks (=1, otherwise 0)	0.035*** (0.017)	0.194 *** (0.017)
Constant	-8.178 *** (0.055)	-8.005 *** (0.017)
Number of Observations	42,275,182	42,275,182
Number of Loans	5,019,467	5,019,467
Number of Firms	3,063,569	3,063,569
Number of Banks	22	22
Log-Likelihood	-4,951,824	-4,937,960
Wald chi-squared	1.06e+06	1.07e+06
Wald Chi-Squared p-value	0.000	0.000

Notes: The table reports the binomial random effects logit regression results. The dependent variable is the probability of a default of a loan borrowed by a firm. Loan Characteristics are the dummy variables indicating the size-group of the loan and the *Collateral*. Firm characteristic includes a dummy variable of the *multiple borrowing* taking on a value of one if the firm borrows from at least 2 banks, zero otherwise. Banks characteristics are dummy variables indicating the connectedness-classification of the lender banks. Analysis covers the period of 2007–2016 in a quarterly frequency. The constant term will determine the probability of default for the reference group, which has the following characteristics: Micro-sized loan whose borrower gets loan only from one bank and whose lender is a weakly-connected bank, and the collateral does not cover the entire loan. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels, ***, **, * indicating the significance level at $p=0.01$, 0.05 , and 0.1 , respectively, are placed adjacently.

Table 2.A1: Mean Comparisons of the Weighted Degree Centrality Measure Among Bank Clusters

Variables	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	All Periods
State-owned Banks	17.74*** (6.071)	42.32*** (5.445)	42.99*** (6.493)	45.48*** (5.010)	46.80*** (6.395)	50.41*** (6.735)	58.55*** (5.654)	64.49*** (5.508)	67.83*** (4.927)	70.92*** (4.939)	48.65*** (4.896)
Large Private Banks	32.14*** (5.620)	65.11*** (5.041)	60.89*** (6.011)	64.78*** (4.639)	68.90*** (5.921)	71.71*** (6.236)	72.09*** (5.235)	77.22*** (5.099)	72.65*** (4.927)	73.93*** (4.939)	63.72*** (4.536)
Large Foreign Banks									72.24*** (7.212)	71.67*** (7.229)	76.23*** (6.038)
Mid-sized Private Banks	14.84** (6.883)	20.27*** (6.174)	18.92** (7.362)	19.00*** (5.681)	26.23*** (7.252)	26.63*** (7.637)	26.53*** (6.411)	27.15*** (6.245)	24.42*** (5.586)	20.82*** (5.600)	19.93*** (4.893)
Mid-sized Foreign Banks	15.32** (5.620)	23.92*** (5.041)	21.52*** (6.011)	22.86*** (4.639)	22.85*** (5.921)	23.32*** (6.236)	24.14*** (5.235)	25.51*** (5.099)	23.37*** (4.561)	19.89*** (4.572)	24.06*** (4.362)
Mid-sized Inv & Dev Banks	3.089 (6.883)	6.755 (6.174)	6.010 (7.362)	6.390 (5.681)	8.338 (7.252)	11.45 (7.637)	14.26** (6.411)	17.38** (6.245)	17.49*** (5.586)	18.18*** (5.600)	10.62* (5.552)
Small Private Banks	4.318 (5.620)	6.408 (5.041)	5.392 (6.011)	4.998 (4.639)	6.386 (5.921)	7.268 (5.916)	6.697 (5.235)	7.200 (5.099)	7.126 (4.927)	7.619 (4.939)	6.921* (3.976)
Small Foreign Banks	2.166 (5.332)	1.684 (4.782)	2.424 (5.703)	2.766 (4.401)	4.498 (5.617)	5.167 (6.236)	7.440 (4.966)	7.542 (4.838)	6.661 (4.164)	6.235 (4.174)	4.171 (3.927)
Constant	0.905 (3.974)	1.068 (3.564)	1.646 (4.251)	1.725 (3.280)	1.755 (4.187)	1.590 (4.409)	1.481 (3.702)	1.095 (3.606)	1.098 (3.225)	1.201 (3.233)	1.339 (3.205)
R-squared [†]	0.717	0.933	0.898	0.943	0.917	0.915	0.942	0.953	0.962	0.964	0.8115

Notes: This table shows the mean comparison of the weighted degree centrality measure among bank clusters. Bank clusters in this table is obtained by the multiplication of the dummy variables which indicate the related bank business and size groupings. Standard errors in parentheses. Constant indicates the coefficient for small investment and development (Inv & Dev) banks. All state-owned banks are large and there is no large investment and development bank in the data set. During the period, there is only one bank of which ownership category was changed in 2015. All estimations except the last model covering whole period are OLS, while the last model is estimated by random effects GLS. [†]represents overall R-squared. ***, **, * indicates the significance level at p=0.01, 0.05 and 0.1, respectively.

Table 2.A2: List of Variables

Variable	Definition	Source
<i>degree</i>	Weighted degree centrality	Authors' calculations
<i>degree_LS1</i>	Weighted degree centrality for micro-sized loans	Authors' calculations
<i>degree_LS2</i>	Weighted degree centrality for small-sized loans	Authors' calculations
<i>degree_LS3</i>	Weighted degree centrality for mid-sized loans	Authors' calculations
<i>degree_LS4</i>	Weighted degree centrality for large-sized loans	Authors' calculations
<i>npl</i>	Non-performing loan ratio	Authors' calculations
<i>npl_LS1</i>	Non-performing loan ratio for micro-sized loans	Authors' calculations
<i>npl_LS2</i>	Non-performing loan ratio for small-sized loans	Authors' calculations
<i>npl_LS3</i>	Non-performing loan ratio for mid-sized loans	Authors' calculations
<i>npl_LS4</i>	Non-performing loan ratio for large-sized loans	Authors' calculations
<i>common_firms1</i>	Number of firms multiple borrow/Number of firms one borrow	Authors' calculations
<i>common_firms2</i>	Sum of loans from multiple borrowing/one borrowing	Authors' calculations
<i>ln(loans)</i>	Natural log of total loans	CBRT-BRSA
<i>coa</i>	Equity/Total asset	CBRT-BRSA
<i>roa</i>	Return/Total asset	CBRT-BRSA
<i>liquid assets</i>	Liquid asset/Total asset	CBRT-BRSA
<i>non-interest expenses</i>	Non-interest expenditures/Total asset	CBRT-BRSA
<i>cds</i>	Credit Default Swap Premium for Türkiye	Bloomberg
<i>gdp growth</i>	Two period lag of Reel GDP growth	Turkish Statistics Institute
<i>aofm</i>	Weighted average cost of funding of the Central Bank of the Republic of Türkiye	CBRT

Notes: This table shows the definitions and the sources of the variables used in the bank level regressions. CBRT is the abbreviation for the Central Bank of the Republic of Türkiye. BRSA is the abbreviation for the Banking Regulation and Supervision Agency of Türkiye.

Table 2.A3: Summary Statistics for the Variables Used in the Baseline Model

Variable		Mean	Std Dev	Min	Max	Obs
<i>degree</i>	overall	27.86	25.75	0.04	95.74	N = 880
	between		24.12	0.81	79.32	n = 22
	within		10.34	-28.43	65.87	T = 40
<i>npl</i>	overall	3.54	2.23	0.11	14.51	N = 860
	between		1.45	1.15	6.57	n = 22
	within		1.72	-0.55	12.71	T-bar = 39
<i>ln(loans)</i>	overall	16.11	1.83	10.17	19.24	N = 880
	between		1.72	12.80	18.22	n = 22
	within		0.70	12.58	17.95	T = 40
<i>eo</i>	overall	13.12	7.14	5.73	95.34	N = 880
	between		4.80	9.13	27.33	n = 22
	within		5.38	-4.56	81.13	T = 40
<i>roa</i>	overall	8.63	6.60	-19.34	50.33	N = 880
	between		4.35	-0.97	14.36	n = 22
	within		5.05	-16.66	44.61	T = 40
<i>liquid asset</i>	overall	26.95	12.97	5.25	75.37	N = 880
	between		8.94	13.21	48.21	n = 22
	within		9.58	-5.59	54.11	T = 40
<i>non-interest expenses</i>	overall	32.03	10.76	13.23	82.73	N = 880
	between		7.99	18.08	46.73	n = 22
	within		7.40	11.39	74.96	T = 40
<i>cds</i>	overall	225.11	66.17	127.03	408.69	N = 880
	between		0.000	225.11	225.11	n = 22
	within		66.17	127.03	408.69	T = 40
<i>gdp growth</i>	overall	4.88	5.17	-14.54	11.80	N = 880
	between		0.00	4.88	4.88	n = 22
	within		5.17	-14.54	11.80	T = 40
<i>aofm</i>	overall	9.58	3.85	5.11	18.06	N = 880
	between		0.00	9.58	9.58	n = 22
	within		3.85	5.11	18.06	T = 40

Notes: This table shows the descriptive statistics of the variables used in the main bank panel regressions whose results are shown in Table 5 and 6. Details of the variables are described in Table 2.A2.

Table 2.A4: Pairwise Pearson's Correlation Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) <i>degree</i>	1								
(2) <i>degree_LS1</i>	0.376 ¹	1							
(3) <i>degree_LS2</i>	0.860 ¹	0.598 ¹	1						
(4) <i>degree_LS3</i>	0.921 ¹	0.323 ¹	0.891 ¹	1					
(5) <i>degree_LS4</i>	0.990 ¹	0.346 ¹	0.845 ¹	0.900 ¹	1				
(6) <i>npl</i>	-0.219 ¹	-0.127 ¹	-0.130 ¹	-0.176 ¹	-0.210 ¹	1			
(7) <i>npl_LS1</i>	-0.075 ²	-0.236 ¹	-0.210 ¹	-0.167 ¹	-0.063 ³	0.231 ¹	1		
(8) <i>npl_LS2</i>	-0.327 ¹	-0.321 ¹	-0.421 ¹	-0.434 ¹	-0.307 ¹	0.373 ¹	0.703 ¹	1	
(9) <i>npl_LS3</i>	-0.313 ¹	-0.249 ¹	-0.336 ¹	-0.389 ¹	-0.296 ¹	0.422 ¹	0.275 ¹	0.625 ¹	
(10) <i>npl_LS4</i>	-0.187 ¹	-0.102 ¹	-0.118 ¹	-0.162 ¹	-0.173 ¹	0.842 ¹	0.021	0.173 ¹	0.347 ¹
(11) <i>ln(loans)</i>	0.866 ¹	0.493 ¹	0.799 ¹	0.820 ¹	0.840 ¹	-0.208 ¹	-0.058	-0.327 ¹	-0.274 ¹
(12) <i>roa</i>	0.291 ¹	0.204 ¹	0.418 ¹	0.346 ¹	0.320 ¹	-0.088 ²	-0.278 ¹	-0.368 ¹	-0.140 ¹
(13) <i>ea</i>	-0.257 ¹	-0.250 ¹	-0.285 ¹	-0.266 ¹	-0.235 ¹	0.070 ²	0.085 ²	0.165 ¹	0.165 ¹
(14) <i>liquid assets</i>	0.123 ¹	0.134 ¹	0.258 ¹	0.079 ²	0.172 ¹	0.104 ¹	-0.019	-0.056	-0.057
(15) <i>non-int exp</i>	-0.377 ¹	-0.116 ¹	-0.274 ¹	-0.229 ¹	-0.380 ¹	0.307 ¹	0.122 ¹	0.097 ¹	0.102 ¹
(16) <i>cds</i>	0.008	0.012	0.017	-0.034	-0.023	-0.052	-0.026	0.021	0.031
(17) <i>gdp growth</i>	0.024	-0.007	-0.036	0.052	0.038	-0.156 ¹	0.047	-0.03	-0.077 ¹
(18) <i>aofm</i>	-0.169 ¹	-0.112 ¹	-0.080 ²	-0.150 ¹	-0.149 ¹	-0.014	-0.187 ¹	-0.237 ¹	-0.113 ¹

Table 2.A4. (continued)

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) <i>degree</i>								
(2) <i>degree_LS1</i>								
(3) <i>degree_LS2</i>								
(4) <i>degree_LS3</i>								
(5) <i>degree_LS4</i>								
(6) <i>npl</i>								
(7) <i>npl_LS1</i>								
(8) <i>npl_LS2</i>								
(9) <i>npl_LS3</i>								
(10) <i>npl_LS4</i>	1							
(11) <i>ln(loans)-0.167²</i>	1							
(12) <i>roa</i>	-0.070 ²	0.297 ¹	1					
(13) <i>eo</i>	0.077 ²	-0.458 ¹	0.189 ¹	1				
(14) <i>liquid assets</i>	0.109 ¹	0.055	0.300 ¹	-0.110 ¹	1			
(15) <i>non-int exp</i>	0.172 ¹	-0.293 ¹	0.062 ³	0.224 ¹	-0.207 ¹	1		
(16) <i>cds</i>	0.055	0.012	-0.093 ¹	-0.098 ¹	0.018	-0.061 ³	1	
(17) <i>gdp growth</i>	-0.127 ¹	0.078 ²	-0.085 ²	-0.070 ²	-0.113 ¹	-0.166 ¹	-0.499 ¹	1
(18) <i>aofm</i>	0.153 ¹	-0.158 ¹	0.193 ¹	-0.013	0.209 ¹	0.135 ¹	0.336 ¹	-0.334 ¹

Notes: This table shows pairwise correlation coefficients between the variables used in the main regressions whose results are shown in Table 5 and Table 6. Details of the variables are described in Table 2.A2. The corresponding significance levels are indicated by ¹, ², ³, showing the significance levels at p=0.01, 0.05, and 0.1, respectively.

Table 2.A5: Tests for Unit Roots in Level - Individual Effects

Variables	LLC 2002	IPS 1997	Fisher-ADF	Fisher- PP
<i>npl</i>	-4.387***	-3.933***	105.346***	88.647***
<i>npl_LS1</i>	-1.983**	-2.215**	81.187***	75.674***
<i>npl_LS2</i>	-0.765	-0.717	63.438**	48.858
<i>npl_LS3</i>	1.719	1.668	44.445	69.131***
<i>npl_LS4</i>	-8.525***	-6.174***	146.159***	124.323***
<i>degree</i>	-3.553***	-4.220***	100.690***	67.427**
<i>degree_LS1</i>	-1.350*	-0.415	46.971	52.580
<i>degree_LS2</i>	-0.857	-0.222	42.840	43.810
<i>degree_LS3</i>	-2.184	-1.198	52.405	45.007
<i>degree_LS4</i>	-6.665***	-5.660***	71.577***	63.950**
<i>ln(loans)</i>	-6.514***	-0.175	66.851**	63.471**
<i>roa</i>	-3.199***	-4.132***	105.052***	50.290
<i>eo</i>	-3.994***	-4.148***	93.882***	73.902***
<i>liquid assets</i>	-2.471***	-1.889**	76.019***	80.454***
<i>non-interest expenses</i>	-3.003***	-4.017***	89.888***	75.229***
Individual Effects, Individual Linear Trends				
<i>npl</i>	-0.969	-0.553	62.857**	52.585
<i>npl_LS1</i>	-2.416***	-2.045**	70.576***	61.608**
<i>npl_LS2</i>	-0.664	-1.292*	59.828*	48.622
<i>npl_LS3</i>	2.623	1.290	52.744	51.514
<i>npl_LS4</i>	-4.961***	-4.192***	115.369***	205.177***
<i>degree</i>	-14.866***	-6.331***	304.732***	52.553
<i>degree_LS1</i>	-0.183	-1.340*	56.302	44.701
<i>degree_LS2</i>	1.763	-1.799**	62.862**	57.998*
<i>degree_LS3</i>	-2.313**	-0.240	158.386 ***	24.013
<i>degree_LS4</i>	-6.678***	-1.993**	293.206***	53.494
<i>ln(loans)</i>	-1.359	-2.710***	91.666***	62.483**
<i>roa</i>	-4.110***	-6.642***	137.948***	52.799
<i>eo</i>	-3.185***	-3.976***	84.817***	70.017***
<i>liquid assets</i>	-3.484***	-3.964***	89.499***	86.423***
<i>non-interest expenses</i>	-15.164***	-13.339***	249.826***	342.866***

Notes: This table shows the unit root test statistics of the variables used in the main regressions whose results are shown in Table 5 and Table 6. Details of the variables are described in Table 2.A2. The corresponding significance levels are indicated by ***, **, and * represents significance level at $p=0.01$, 0.05 , and 0.10 , respectively. Levin, Lin, and Chu (LLC 2002) tests for common unit root, while Im, Pesaran, and Shin (IPS 1997), ADF-Fisher and PP-Fisher tests assume for individual unit root. Fisher-ADF and Fisher-PP refer to Fisher-Augmented Dickey-Fuller and Fisher-Phillips-Perron, respectively. Lag lengths are determined by Schwarz Information Criterion (SIC) for Levin- Lin-Chu, Im- Pesaran-Shin, Fisher- ADF tests. Automatic bandwidth selection is based on Newey-West and Bartlett kernel for Fisher-PP. We repeat the same tests for unit roots in first difference. To save space, we do not report but all variables in their first difference are found stationary at 0.01 significance level.

CHAPTER III

MARKET REACTIONS TO THE TREASURY-BACKED CREDIT GUARANTEES

3.1. Introduction

The uncertainties in global markets, geopolitical developments, and weakening capital flows engendered volatility in exchange rates, higher risk premiums, and tighter financing conditions for Turkish banks in 2016.¹ The prime minister announced new policies to relieve the liquidity crunch, encourage investment, and boost employment on December 8, 2016. The centerpiece of the program was the 12.5-fold increase in the Treasury support for the Credit Guarantee Fund of Türkiye (CGF) from 20 to 250 billion TL (5.5 to 69.3 billion USD) (Anadolu Ajansı, 2016). CGF strives to increase funding particularly for Small and Medium Enterprises (SMEs) through loan guarantees that promise partial repayment in case of default. The increase in Treasury support made CGF one of the largest of its kind among the OECD countries (OECD, 2019). We investigate how investors priced the economic benefits and costs of this unprecedented increase in Treasury support.

Honohan (2010) and Beck et al. (2010) explain how privately funded credit guarantee schemes may generate value due to their information advantages, diversification opportunities, and regulatory arbitrage. First, a guarantor that benefits from the collective information of its participating lenders might enjoy lower costs when evaluating borrower risk than any individual lender. Second,

¹This chapter is published in Topaloğlu-Bozkurt and Tanyeri- Günsür (2023).

guarantors may better diversify risk than a single lender with geographically or industry-concentrated borrowers. Third, a guarantor may benefit from lending regulations that bind its participants but not the guarantor. Then, what value does government backing add to credit guarantee schemes? Public credit guarantee programs may counterbalance impermanent credit crunches arising from sudden spikes in uncertainty. Uncertainty increases and liquidity dries up during an economic and political crisis. Politicians might also support credit guarantee schemes to reap the benefits from increased lending in the short run. The fiscal costs of credit guarantee schemes may only be apparent in the long run. The use of government-backed credit guarantee programs as a counter-cyclical macro-prudential tool increased after the global financial crisis (Gai et al., 2016; Agnese et al., 2019). The increase in Treasury support of the Turkish credit guarantee fund also followed a period of political and economic uncertainty.

This chapter relates to research on public credit guarantee schemes by focusing on investors' perceptions of the net benefits of the proposed program. There is extensive literature on how regulators use monetary and fiscal policy to shape expectations and investor behaviour (Bernanke and Kuttner, 2005; Afonso and Sousa, 2011; Croce et al., 2012; Belo and Yu, 2013; Hu et al., 2018). The increase in Treasury support for CGF as a counter-cyclical macro-prudential tool aimed to generate a transitory credit expansion. The information released in the announcement affected investor expectations. Investors trade based on their updated expectations. We contribute to the literature by focusing on how change in investor expectations was reflected in stock returns on the announcement date.

We employ event study methodology to estimate how stock market investors priced this unprecedented increase in Treasury support at announcement. The 9-day cumulative abnormal returns centered on the announcement for 416 Turkish firms listed on the exchange prove significant at 5.72 percent. The positive and significant

abnormal returns indicate that investors ex-ante priced the expected positive policy effects before observing any change in the availability and cost of CGF-guaranteed loans. Our results suggest that the information released in the announcement, in line with the stated aim of the program, positively affected investor expectations.

3.2. Background on the Credit Guarantee Fund of Türkiye

CGF is “a guarantor for SMEs and non-SME enterprises that cannot get a loan due to insufficient collateral” (CGF, n.d.-a). CGF, founded in 1991, provided the first guarantee in 1994. CGF is a joint stock company with 34 shareholders. The largest shareholders are The Union of Chambers and Commodity Exchanges of Türkiye (TOBB) and the Small and Medium Enterprises Development Organization of Türkiye (KOSGEB), with 28 percent shares each. Twenty-nine banks (who control more than 95 percent of Turkish banking assets), each with 1.5 percent shares, are the other significant shareholders (CGF, n.d.-b). CGF enjoys private and public funding from its shareholders and the Turkish Treasury.

Political and economic uncertainty resulting from local and global events, such as the July coup attempt, the Brexit referendum in June, and the US elections in November, adversely affected the Turkish credit market in 2016. The government deliberated on policies to alleviate the liquidity crunch in 2016. The Economic Coordination Committee declared that new fiscal policies concerning banks, financial and labor markets will be publicized in the week following their meeting on December 2, 2016 (TRT Haber, 2016). The Prime Minister announced the increase in the guarantee limit of the Treasury-backed CGF, the interest-free loan support program of the Small and Medium Enterprises Development Organization (KOSGEB), changes in the corporate tax rate on December 8, 2016 (Anadolu Ajansı, 2016). The shareholder banks and CGF signed The Amendment for

Uniform Guarantee Protocol on March 17, 2017 . According to the new Protocol, banks started to grant loans on March 20, 2017.² The Protocol initially increased the CGF guarantee limit from 50 to 200 billion TL. The Protocol allowed for a “portfolio” model (the portfolio guarantee system or PGS) of lending where lenders conduct the risk assessment without additional assessment by CGF.³

The Protocol also mandated risk sharing between CGF and the lender. The lender bore the default costs when the ratio of non-performing loans in its CGF loans exceeds seven percent. Beck et al. (2010) discuss the importance of guarantee coverage ratios and risk sharing between the lender and the guaranteeing agency. Risk sharing between the lender and the guarantor may limit the adverse selection and moral hazard costs. Three new CGF schemes followed in 2018 and 2019. We focus on how stock market investors reacted to the first CGF scheme since it is the first and reveals the most significant increase in Treasury support.

3.3. Research Method

We use the event study methodology of Brown and Warner (1985) to analyze market reaction to the announcement of the CGF program. Identifying the first public release of information is essential in the event study method. We used Factiva (2019), Google, and Wayback Machine searches to identify the day the public learns of the CGF Protocols. We also drew upon a Turkish news channel, NTV’s “Newspaper Headlines of the Day” service (2018), and the news section of the CGF website to check the results.

²The Decree about the Treasury Support are available from the Official Gazette (<https://resmigazete.gov.tr/eskiler/2017/03/20170310.pdf>) and the CGF website (<https://www.CGF.com.tr/index.php/tr/duyuru-haber/CGF-den-haberler/82-isletmelere-200-milyon-tl-ye-kadar-CGF-teminati>).

³The Protocol set the PGS loan principal limit at 50 million TL. The credit approval of loans over 50 million TL must go through CGF and the lender. The Protocol specified guarantee ratios ranging from 85 to 100 percent for different loan categories (CGF, n.d.-c).

We download returns $R_{i,t}$ for all stocks listed on Borsa Istanbul using Bloomberg. Event day 0 (Day 0) is the announcement day, December 8, 2016. The estimation window $([-272, -21])$ covers the 252 trading days starting 272 days before the announcement and ending 21 days after. The event window $([-20, 20])$ covers the 41 trading days centered around the announcement. We calculate abnormal returns $A_{i,t}$ for stock i on day t as:

$$A_{i,t} = R_{i,t} - \bar{R}_i, \text{ where } \bar{R}_i \text{ is mean returns for stock } i \text{ in the estimation window.} \quad (3.1)$$

We test the significance of abnormal returns using the t-statistic:

$$t = \frac{\bar{A}_t}{\hat{S}(\bar{A}_t)} \quad (3.2)$$

where

$$\hat{S}(\bar{A}_t) = \sqrt{\frac{\sum_{-272}^{-21} (\bar{A}_t - \bar{\bar{A}})^2}{251}} \quad (3.3)$$

and

$$\bar{\bar{A}} = \sum_{-272}^{-21} \frac{\bar{A}_t}{252} \quad (3.4)$$

and

$$\bar{A}_t = \sum_{i=1}^N \frac{A_{i,t}}{N} \quad (3.5)$$

where N is the number of firms.

We require stocks to have returns on at least 90 days in the estimation window.⁴

The resulting sample covers 416 firms. Three hundred forty-five are non-financial firms, and 71 are financial services companies (16 of which are banks).

⁴Investor anticipation and information leaks may affect the event study method (Cornett et al., 2011; Fescioglu-Unver & Tanyeri, 2013; Tanyeri-Günsür & Bulut, 2022), particularly in developing countries such as Türkiye (Arslan and Simsir, 2016; Hekimoğlu & Tanyeri, 2011; Yılmaz & Tanyeri, 2016, Tanyeri, et al., 2022).

3.4. Results

Table 3.1 and Table 3.2 report cumulative abnormal returns for different event windows around the announcement in the full sample and sub-samples of firms, banks, and non-bank financial institutions, respectively. The Economic Coordination Committee met after stock-market closing on Friday, December 2, 2016, to discuss economic conditions and the government initiatives. The prime minister announced the increase in Treasury support for CGF on Thursday, December 8, 2016, in a press meeting. Table 3.1 reports that for the 416 firms and financial institutions, the 3-day, 5-day, 7-day, 9-day and 11-day CARs prove positive and significant at 1.00, 3.03, 4.67, 5.72 and 4.27 percent, respectively. The $[-4, +4]$ event window covers the four trading days before the formal announcement on which information about the CGF policy may have leaked, the announcement day, and the four trading days following the announcement. Table 3.2 reports that the 3-day, 5-day, 7-day, 9-day and 11-day CARs for the 345 firms, 16 banks, and 55 non-bank financial institutions also prove positive and significant. Investors perceived the increase in Treasury support to benefit both firms and financial institutions. On one hand, firms may benefit as the potential recipients of funding. On the other hand, financial institutions may benefit as intermediaries in the allocation of the funding.

Khwaja and Mian (2005), Beck et al. (2010), Honohan (2010), Gai et al. (2016), and Agnese et al. (2019) agree to the easing of impermanent credit crunches as the main advantage, and incentives to reap short-term political benefits from increased lending without proper accounting of long-term costs as the disadvantage, of public guarantee schemes. Local and global political uncertainty around the Turkish coup attempt in July, the Brexit referendum in June, and the US elections in November marked 2016. The government addressed the liquidity squeeze by increasing

Table 3.1: Cumulative Abnormal Returns Around the Announcement Day in the Full Sample

Window	CARs	t-statistics	Brown & Warner t-statistics
Day 0	-0.09	-0.59	-0.08
[-1,1]	1.00	3.81***	0.57
[-2,2]	3.03	8.55***	1.33
[-3,3]	4.67	10.47***	1.73 ^a
[-4,4]	5.72	12.13***	1.87 ^a
[-5,5]	4.27***	8.37***	1.26***

Notes: Table reports CARs (in percent) using windows of one day (Day 0), three days (-1,1), five days (-2,2), seven days (-3,3), nine days (-4,4), and 11 days (-5,5) around the announcement in the full sample. Corresponding t-statistics and Brown and Warner (1985) t-statistics are in the last two columns. *, **, *** and a, b, c indicates statistical significance at 10%, 5%, and 1%, respectively, for standard cross-sectional t-statistics and Brown and Warner (1985) t-statistics, respectively.

Table 3.2: Cumulative Abnormal Returns Around the Announcement Day in Industry Sub-samples

Window	CARs	t-statistics	Brown & Warner t-statistics
Day 0	0.01 (0.04)	-0.10* (0.57)	-0.67 (-1.60)
[-1,1]	1.06 (3.65)***	1.11 (2.45)**	0.58 (0.75)
[-2,2]	3.23 (8.15)***	2.89 (4.34)***	1.85 (1.87)*
[-3,3]	4.90 (9.92)***	3.99 (5.05)***	3.39 (2.59)***
[-4,4]	5.93 (11.05)***	4.96 (5.25)***	4.64 (4.03)***
[-5,5]	4.42 (7.69)***	5.15 (5.30)***	3.07 (2.28)***

Notes: Table reports CARs (in percent) using windows of one day (Day 0), three days (-1,1), five days (-2,2), seven days (-3,3), nine days (-4,4), and 11 days (-5,5) around the announcement in industry sub-samples. Corresponding t-statistics are in parenthesis and the corresponding significance levels, ***, **, * indicating the significance level at p=0.01, 0.05, and 0.1, respectively.

Treasury support of CGF. The positive and significant abnormal returns around the announcement suggest that investors perceived the benefits of the Treasury backing to outweigh the costs.

The announcement emphasized the policy aim of relieving the liquidity crunch, encouraging investment, and boosting employment in the announcement (Anadolu Ajansı, 2016). First, we refer to the TCMB Bank Loan Tendency Survey to explore whether bank lending standards changed following the announcement. Lending standards tightened during 2015 and 2016. The tightening eased in 2017 following the CGF announcement.⁵ Second, the number of firms approved for CGF-guaranteed loans increased from 4,376 in 2015 to 297,682 in 2017. The corresponding increase in loan volume was from 2.4 billion TL (0.8 billion USD) to 208 billion TL (55.2 billion USD) (CGF Annual Report, 2015 and 2017). Third, Akçigit et al. (2021) found that firms receiving CGF loans enjoyed higher sales, increased employment, and decreased default probability relative to a control group that did not. The easing in lending standards, the increase in firms receiving CGF loans, and the resulting positive firm outcomes all point to the successful realization of program aims. We show that investors positively reacted to the announcement before observing the success or failure of the program. The results suggest that investors anticipated positive program outcomes and that expectations improved at announcement.

3.5. Conclusion

We analyze investor response to the unprecedented increase in the Treasury support for loan guarantee schemes in a developing country, Türkiye. The government aimed to stimulate economic activity by alleviating financing constraints with public-funded loan guarantees. Investors welcomed the increase in

⁵Supplement 1 describes the Bank Loan Tendency Survey in detail in the Appendix.

the Treasury support for loan guarantee schemes. The 3-day, 5-day, 7-day, 9-day and 11-day cumulative abnormal returns prove positive and significant around the announcement. Investors, at the announcement, perceived the benefits from anticipated new lending to Turkish firms to outweigh the future fiscal costs. The positive stock market reaction suggests that the government improved investor expectations. Güngör and Sümer (2018) report that about one-third of the CGF loan beneficiaries received loans for the first time. The proportion of firms securing loans for the first time suggests that the policy aim of providing funds to credit-constrained Turkish firms proved successful. The ex-post outcomes of firms receiving CGF-guaranteed loans corroborate the ex-ante positive investor reaction to the increase in Treasury support. However, both our results based on the announcement date and the results on ex-post program outcomes (Güngör and Sümer, 2018; Akçığit et al., 2021) at most cover the two years following the announcement. Future work that focuses on the fiscal costs of the CGF program may need to consider the longer horizon.

CHAPTER IV

HOW DID CREDIT GUARANTEE FUND SUPPORTS AFFECT THE BANK-LOAN NETWORK?

4.1. Introduction

In this chapter, we extend our sample period to study how public loan guarantee scheme expanded in 2017 changed the bank-loan network in Türkiye. We believe that the period of credit guarantee funds (CGSs) after 2017 deserve special attention considering the fact that number of firms in the credit market and the amount of loans provided by the banks significantly changed.

Credit guarantee funds (CGSs) provide guarantees to those who cannot access to credit. CGSs have a credit risk mitigating function for lenders as they reduce the credit risk transferred from firms to financial intermediaries resulting from information asymmetry. They are generally used to ease financial constraints for small and medium-sized enterprises that have difficulty in accessing credit because of insufficient collateralization, limited credit history and lack of expertise needed to produce sophisticated financial statements (OECD, 2018). To ease financial constraints for SMEs, the Council of Ministers in Türkiye decided on more than twelve-fold increase in guarantee limit by Credit Guarantee Fund of Türkiye (Kredi Garanti Fonu, CGF henceforth) towards the end of 2016. The related protocol was signed between CGF and banks as of March 17, 2017, and banks started to grant

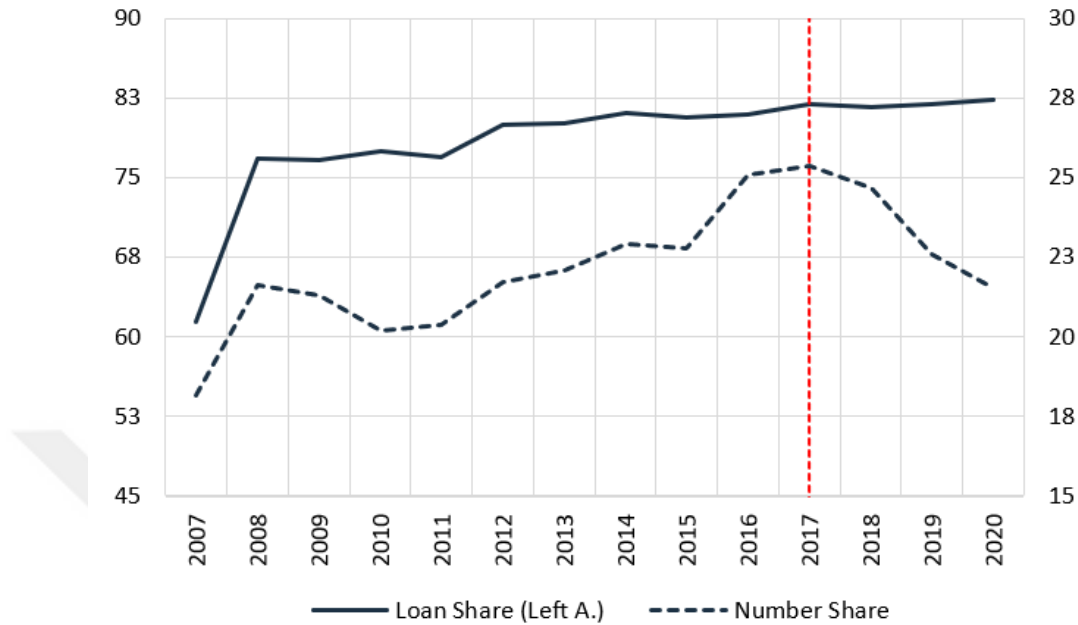


Figure 4.1: The Share of Firms Borrowing from Multiple Banks

Notes: Dashed line shows the share of firms borrowing from more than one bank over total firms (in percent, at right axis) and the black line shows the share of loans borrowed by firms with multiple banks (in percent, at left axis).

loans according to the new protocol since then.

The new policy resolved the collateral requirements of the banks in Türkiye , which increased most in 2016 since the global financial crisis, mostly for the firms that have already access to bank loans. In addition, about one third of the firms received loans for the first time via this facility (Güngör and Sümer, 2018). The loan supply was also supported by the changes in the credit risk weights policy. The credit risk weights of loans guaranteed by the Treasury-backed CGF guarantees were determined as zero allowing banks to grant credit without reserving additional equity. Thus, by the introduction of Treasury backed CGF guarantees as of March 2017, the total volume of banking sector’s outstanding credits were increased by 10 percent.

CGF schemes provided a substantial amount of surety not only for SMEs but also

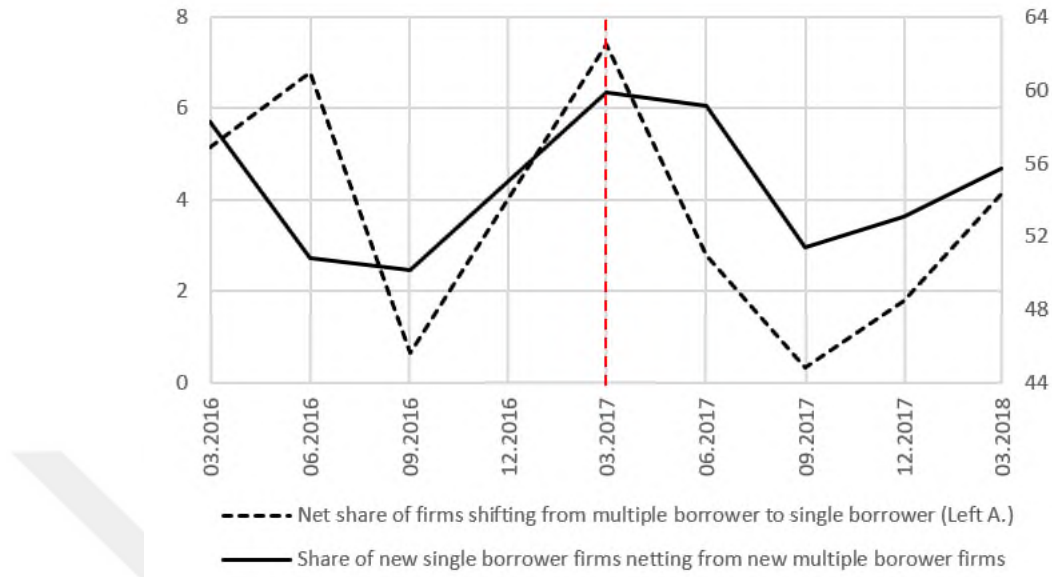


Figure 4.2: The Changes in the Share of Firms Borrowing from Multiple Banks After CGF Supports

Notes: Dashed line shows the difference between the share of existing firms switching from borrowing from more than one bank to borrowing from one bank and the share of existing firms switching from borrowing from one bank to borrowing from more than one bank (in percent, at left axis). Black line shows the difference between the share of new entrant firms that borrow from one bank and those that borrow from more than one bank (3-months average, in percent, at right axis) and the black line shows the share of loans borrowed by firms with multiple banks (3-months average, in percent, at right axis).

large firms in Türkiye. More than 75 percent of Treasury-backed CGF guarantees were given to SMEs. Nonetheless, the amount guaranteed was also very high for large firms, as it constituted almost 25 percent of the credit guarantees of 200 billion TL. The second CGF package, which amounts to 55 billion TL of guarantee backed by the Treasury including the repayments of the first package, is launched in January 2018 and mainly allocated to SMEs. This scheme had a special support for business women and young entrepreneurs who generally own SMEs rather than large firms.

In Türkiye, the evidence shows that CGF packages solved the collateral problem of existing companies (Güngör and Sümer, 2018). Figure 4.1 presents that though the share of loans borrowed by firms with multiple banks slightly increased, the share

of these firms over total firms decreased amid the Treasury support of CGF guarantees. Figure 4.2 indicates that the decrease in the share of the multiple borrowers is resulted from two facts. First, among the new borrowers, the number of firms financed by only one bank is much more than those financed by multiple banks. Second, shifting of existing multiple borrower firms (common firms) to single borrower firms (borrow only from one bank) is higher than the reverse case. Based on these information, we question the impact of CGF schemes on the loan network of banks in Türkiye. We hypothesize that CGF packages are expected to decrease the bank connectedness originating from the common borrower firms. First, we investigate whether these CGF schemes have resulted in a significant change in the bank loan network in Türkiye. Moreover, we study whether the impact of loan centrality on bank portfolio riskiness changed with these schemes. Our results show that CGF schemes affect the connectedness of banks differently.

While CGF schemes significantly increases the connectedness of large banks and small banks, they do not have a significant impact on mid-size banks. In addition, the connectedness of state-owned banks and private domestic banks is significantly increased with the CGF schemes. Moreover, CGF schemes increase the centrality of the strongly connected banks, while they do not have a significant impact on the centrality of the moderately or weakly connected banks. Finally, we find that the CGF schemes support the decreasing impact of the connectedness of the banks on the bank loan portfolio. On the other hand, we document that CGF schemes increase the loan portfolio riskiness of the banks.

The outline of the chapter is as follows: Section 2 summaries the related literature. Section 3 introduces the data, and presents the bank loan networks after CGF supports. Section 4 documents the empirical results, and section 5 concludes the chapter.

4.2. Literature Review

The main function of the financial intermediaries is known to reduce the asymmetric information between the lender and the borrower which causes adverse selection and moral hazard problems (Dimond, 1984; Millon and Thakor, 1985; Boot et al., 1991). Banks may solve asymmetric information problems through ex-ante screening (for adverse selection problem) and ex-post monitoring (for moral hazard problem). In the literature, there are evidence that moral hazard and adverse selection problems are also alleviated by collateral (Bester, 1985; Rajan and Winton, 1995). However, compared to larger firms, SME's, in particular, cannot benefit from the advantages of using collateral. These firms lack of enough collateral and hence banks, in general, require more borrower-special information to lend to SMEs (Elyasiani and Goldberg; 2004). To compensate for SMEs' lack of collateral and creditworthiness, credit guarantee schemes by governments (public CGSs) seems to be a "right" policy tool to reduce credit risk for banks and hence expand their lending (Vogel and Adams, 1997).

Since global financial crisis, the use of public guarantees to provide access to finance for SMEs increased significantly in several countries (Gai et al, 2016). In addition, recently credit guarantee schemes have also been used as a counter cyclical policy tool (Agnese et al, 2019). In line with these developments, there are many studies focusing on the impacts of CGF schemes on banks and SMEs' access to finance in both developed and developing countries.

As an examples of studies in developing countries, Gai, Lelasi and Roslini (2016) examine the impacts of direct public guarantees to SMEs or a counter-guarantee to mutual guarantee instructions (MGIs) by the Italian national credit guarantee program (Fondo Centrale di Garanzia – Central Guarantee Fund) on the default risk of counter-guaranteed loans in Italy. According to their firm-level empirical

results, both the level of public aid and the volume of an MGI's counter-guaranteed portfolio are positively related to the default risk of public guarantees. Similarly, by employing difference in difference methodology, Bertoni et al (2018) provide evidence from France, as having second highest guarantee schemes after Italy, that SMEs benefitting from EU-guaranteed loans experienced additional growth in assets, sales and employment and also lower rates of defaults compared to firms in control groups. Moreover, the productivity of these beneficiary firms increases significantly, though there exist adjustment costs in the short and medium term. On the other hand, Wilcox and Yasuda (2019) investigate the impacts of government guarantees of credits to SMEs on banks' risk taking and non-guaranteed lending in Japan. They find that loan guarantees raise banks' risk-taking behavior as a result of the increases in credit-guaranteed loans in their credit portfolio. In addition, contrary to existing literature, they conclude that additional loan guarantees tended to increase, rather than decrease, banks' non-guaranteed lending, specifically if banks started with relatively low volume of guaranteed loans and banks with higher capital ratios give more non-guaranteed credits.

On the other hand, studies in the developing economies show that both firms and banks benefit from these CGF guarantees though there are some costs of these schemes. Liang et al (2017)'s article is one of the studies focusing on the effects of credit guarantee schemes in an emerging economy, specifically South Korea. Similar to Wilcox and Yasuda, they analyze the impacts with regard to banks, namely banks' efficiency. By utilizing stochastic frontier approach on 14 banks over the period 2001–2010, they find that when banks increase their loans to SMEs, banks cost efficiency diminishes as a result of the information asymmetry. On the other hand, with the rising share of credit guarantees, which enables banks to have SMEs' credit risk information, the cost efficiency of banks improves. Moreover,

employing propensity score matching methodology to a large sample of guaranteed and non-guaranteed firms' loans from 2000 to 2003 in South Korea, Oh et al. (2009) find that credit guarantees significantly affected firms 'ability to maintain their size, and increase their survival rate and because of the adverse selection problem, firms with lower productivity were receiving guarantees.

Employing a comprehensive set of selected OECD countries for the period of 2007 to 2016, Agnese et al. (2019) show that the impact of Credit Guarantee Schemes (CGS) on SMEs bankruptcies is mixed depending on the country. For instance, for Korea and US, the impact is negative, meaning that with the increasing CGS the SMEs bankruptcies fall, while it is positive for Italy, Japan, Spain and Türkiye, i.e. there is positive association between the CGS volume and bankruptcy of SMEs.

There are a number of studies regarding credit guarantee schemes in Türkiye. For example, Akçiğit et al. (2019) find that Treasury backed CGF loans during the end of the first quarter in 2017 have several positive impacts on the firm's performance such as raising the employment rate by 17 percent, sales by 70 percent and reducing firms' probability of default by 0.6 percentage point compared to counterfactuals. Similarly, Yağcı (2019) examines the CGF guarantees in Türkiye from a comparative historical case study perspective. According to him, the lack of alternative financing arrangements, high commercial interest rates, over-reliance on the banking sector and Basel III requirements of high capital buffers are the main challenges for SMEs' credit access. On the other hand, by employing Granger causality method, Yıldırım et al (2015) show that Credit Guarantee Fund schemes caused expansion of commercial loan since 2006, which also had a positive and significant impact on new investments in Türkiye.

4.3. Data

Our sample contains 22 banks and covers the period from 2007Q1 to 2018Q1 . The beginning of the sample period is determined by the availability of high quality data. We end the sample in 2018Q1 to avoid the negative impact of currency fluctuations on the credit market. In this chapter, we use the same dataset in Chapter 2, but we extend the sample period to 2018Q1. We also use the same variables in the second chapter. However, in this chapter, we introduce a time dummy variable indicating the period when CGF supports are implemented between 2017Q2 to 2018Q1.

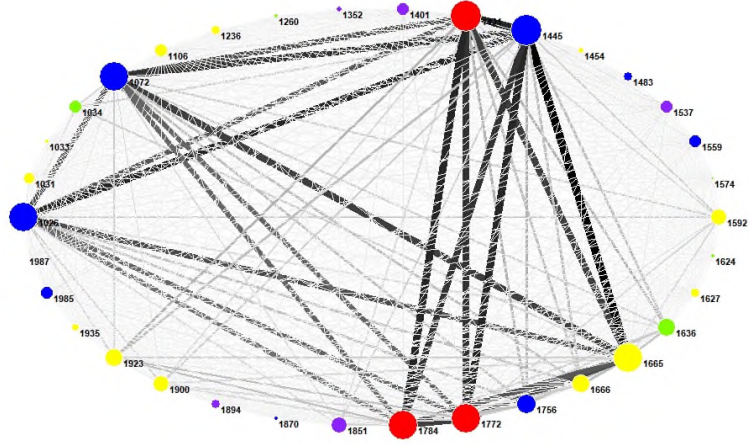
CGF is the only institution in Türkiye that provides guarantees to ease SME and non-SME access to finance. It provides a partial guarantee for a commercial credit for all TL or foreign currency cash and non-cash loan needs of the firms. The bank loan can be used for either operational or investment purposes. CGF is established in 1991 as a state-fund program. In 2016, by the extreme global financial conditions, especially for the emerging and developing markets, the decision of the Treasury support to credit guarantee agencies renewed. With the amendment of decision entered into force on 10.03.2017, the total amount of indemnities given by CGF has increased to TL 250 billion. During our sample period, two credit guarantee schemes were implemented to overcome the downturn trend in credit growth emerging from the second half of 2016. First guarantee package (CGF-I) amounts to TL 200 billion and the second package (CGF-II) includes TL 55 billion of guarantee backed by Treasury. On the other hand, the upper limit of compensation was determined as 7 percent of the guarantee for each credit institution. In other words, the lender bank bore the default costs when the ratio of non-performing loans in its CGF loans exceeds 7 percent.

4.4. Bank Loan Network After CGF Supports

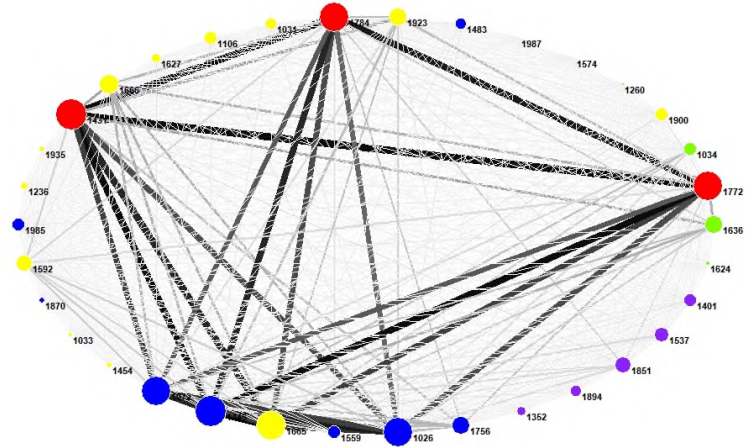
Figures 4.3 and 4.4 represent the networks of banks based on their lending to the same firms in 2016 and 2017, respectively. The thickness of the edges shows the strength of the connections between the nodes (banks) and the size of the nodes indicate the bank's connectedness (weighted degree) due to lending to common firms. As the figures indicate, the connectedness of the banks is slightly increased in 2017 compared to 2016.

The color of the vertices shows the groups of the banks according to their business model: state-owned, private domestic, foreign, development and investment, and participation (Islamic) banks. As represented by the figures, the connectedness of banks differs according to bank's business groups. It is highest in the state-owned banks whereas it is lowest in the development and investment banks.

As in chapter 2, we group the banks according to their asset size as large, mid-sized, and small banks. Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks. Table 4.1 presents the impact of CGF schemes on the centrality of the banks, i.e. weighted degree of the banks, emerging from their common borrowers across bank-size groups. Column 1 indicates that the degree of the banks changes significantly across the bank size groups. The average degree of large banks and mid-sized banks significantly higher than that of small banks. Estimation results across the sub-samples according to banks' size groups are represented in Columns 2 to 5. CGF significantly increases the degree of the large banks, while it does not have an impact on the degree of the Mid-sized banks. Though the impact of CGF on the degree of small banks seems to insignificant in the first regression (Column 1), it is significantly positive in the fourth estimation (Column 4).



(a) Projected Loan Network of Banks as of December 2016



(b) Projected Loan Network of Banks as of December 2017

Figure 4.3: Projected Loan Networks According to Banks' Weighted Degree as of December 2016 and 2017.

The figure presents the networks of banks in Türkiye as of December 2009 based on their lending to the same firms. Vertices (nodes) show the banks. The color of the vertices shows the groups of the banks according to their business model; red, blue, yellow, and green demonstrate state-owned, private domestic, foreign, and development and investment banks, respectively. Since the data about participation (Islamic) banks starts in 2010, we have only four business group before then. The size of the vertices indicates the size group of the banks: large, mid-sized, and small banks. The thickness of the edges between the vertices shows the strength of the connections between the nodes (banks) due to lending to common firms. The figure above (a) demonstrates the connectedness measured by our method; weighted degree, while the figure below (b) shows the connectedness measured by degree. The thickness of the edges in the networks is not comparable between different methods but does indicate the relative degree of the banks within the same network. The figures are drawn by Pajek.

Table 4.1: Impact on CGF Schemes on Weighted Degree Across Bank-Size Groups

Variables	All Banks <i>degree</i>	Large Banks <i>degree</i>	Mid-Sized Bank <i>degree</i>	Small Banks <i>degree</i>
<i>CGF</i>	1.184 (1.779)	15.85*** (3.405)	-1.638 (1.071)	1.184** (0.465)
<i>Large Banks</i>	52.92*** (3.812)			
<i>Mid-Sized Banks</i>	17.56*** (3.986)			
<i>CGF*Large Banks</i>	14.66*** (2.690)			
<i>CGF*Mid-Sized Banks</i>	-2.821 (2.813)			
<i>Constant</i>	6.351** (2.521)	59.27*** (4.172)	23.91*** (2.638)	6.351*** (1.429)
Observations	990	315	270	405
Number of Banks	22	7	6	9

Notes: Table shows the panel data random effects estimation results for the impact of CGF schemes on the weighted degree measure of banks. CGF is a time dummy variable that equals one from 2017Q2 and onwards, and zero otherwise. We classify banks as follows: Large banks have assets of more than five percent of the banking sector assets, while mid-sized banks have less than five percent and more than 0.8 percent of the banking sector assets and the remaining banks are small banks. Large banks and Mid-Sized Banks are the dummy variables indicating whether a bank belongs to the related size-grouping. Constant in column (1) shows the group of small-banks. Standard errors are shown in parentheses. ***, **, * indicate the significance level at $p=0.01$, 0.05 , and 0.1 , respectively.

Table 4.2: Impact of CGF Schemes on Weighted Degree Across Bank-Business Groups

<i>Variables</i>	All Banks <i>degree</i>	State Owned <i>degree</i>	Private Domestic <i>degree</i>	Foreign <i>degree</i>	Dev.& Investment <i>degree</i>
<i>CGF</i>	-0.762 (3.761)	25.21*** (5.500)	3.580* (2.002)	-0.916 (0.692)	-0.762*** (0.276)
<i>State-Owned Banks</i>	48.85** (20.15)				
<i>Private Domestic Banks</i>	25.24 (16.51)				
<i>Foreign-Owned Banks</i>	25.57 (16.53)				
<i>CGF*State-Owned Banks</i>	25.97*** (4.855)				
<i>CGF*Private Domestic Banks</i>	5.085 (4.206)				
<i>CGF*Foreign-Owned Banks</i>	1.035 (4.179)				
<i>Constant</i>	1.705 (15.61)	50.55*** (4.929)	28.96*** (7.778)	20.92*** (5.942)	1.705*** (0.491)
Observations	990	135	434	331	90
Number of Banks	22	3	13	10	2

Notes: Table shows the panel data random effects estimation results for impact of CGF schemes on the weighted degree measure of banks. CGF is a time dummy variable that equals one from 2017Q2 and onwards, and zero otherwise. We classify banks according to their business model as: state-owned, private domestic, foreign, and development and investment banks. State-Owned Banks, Private Domestic Banks, and Foreign-Owned Banks are the dummy variables indicating whether a bank is in the related bank business-grouping. Constant in the column (1) shows the group of development and investment banks. Standard errors are shown in parentheses. ***, **, * indicate the significance level at p=0.01, 0.05, and 0.1, respectively.

Table 4.3: Impact on CGF Schemes on Weighted Degree Across Bank-Connectedness Groups

<i>Variables</i>	All Banks <i>degree</i>	Strongly Connected <i>degree</i>	Moderately Connected <i>degree</i>	Weakly Connected <i>degree</i>
<i>CGF</i>	0.205 (2.026)	13.53*** (2.773)	-0.629 (0.719)	0.291 (0.455)
<i>Strongly Connected</i>	31.08*** (2.166)			
<i>Moderately Connected</i>	13.94*** (1.999)			
<i>CGF*Strongly Connected</i>	15.45*** (2.866)			
<i>CGF*Moderately Connected</i>	1.990 (2.810)			
<i>Constant</i>	12.25*** (1.897)	48.05*** (2.954)	17.96*** (1.819)	5.244*** (1.376)
Observations	990	374	278	338
Number of Banks	22	12	12	8

Notes: Table shows the panel data random effects estimation results for impact of CGF schemes on the weighted degree measure of banks. CGF is a time dummy variable that equals one from 2017Q2 and onwards, and zero otherwise. We classify banks according to their connectedness-classification as follows: Strongly connected banks, moderately connected banks, and weakly connected banks. The related dummies take a value of one if a bank belongs to the related group, zero otherwise. Constant in the column (1) shows the group of weakly connected banks. Standard errors are shown in parentheses. ***, **, * indicate the significance level at $p=0.01$, 0.05 , and 0.1 , respectively.

Similarly, Table 4.2 shows the impact of CGF schemes on the banks' weighted degree across bank-business groups. The average degree of state banks (public banks) significantly higher than that of development and investment banks. In addition, the impact of CGF schemes is significantly higher in public banks compared to development and investment banks (Column 1). On the other hand, estimation results across the sub-samples according to banks' business groupings (Column 2-Column 5) show that CGF schemes significantly increase the average degree of public banks and private domestic banks, while their impact on the

Table 4.4: Estimation Results of the Baseline Model

<i>Variables</i>	<i>All</i>		<i>Micro-Size Loans</i>		<i>Small-Size Loans</i>		<i>Medium-Size Loans</i>		<i>Large-Size Loans</i>	
	<i>npl</i>	<i>npl</i>	<i>npl_LS1</i>	<i>npl_LS1</i>	<i>npl_LS2</i>	<i>npl_LS2</i>	<i>npl_LS3</i>	<i>npl_LS3</i>	<i>npl_LS4</i>	<i>npl_LS4</i>
<i>degree</i>	-0.049*** (0.007)	-0.049*** (0.007)								
<i>CGF</i>	1.332*** (0.235)	1.399*** (0.304)	14.32*** (1.612)	17.22*** (1.767)	13.78*** (1.218)	20.49*** (1.398)	1.297* (0.692)	2.978*** (0.872)	0.668*** (0.237)	1.055*** (0.305)
<i>CGF*degree</i>		-0.002 (0.007)								
<i>degree_LS1</i>			-1.940*** (0.362)	-1.309*** (0.395)						
<i>CGF * degree_LS1</i>				-1.522*** (0.393)						
<i>degree_LS2</i>					-0.365*** (0.081)	-0.197** (0.081)				
<i>CGF * degree_LS2</i>						-0.767*** (0.087)				
<i>degree_LS3</i>							-0.209*** (0.021)	-0.205*** (0.021)		
<i>CGF * degree_LS3</i>								-0.0761*** (0.024)		
<i>degree_LS4</i>									-0.042*** (0.006)	-0.041*** (0.006)
<i>CGF*degree_LS4</i>									-0.011**	(0.006)
<i>lnloans</i>	0.668*** (3.126)	0.667*** (3.128)	0.850 (22.30)	0.605 (22.15)	0.315 (16.06)	0.541 (15.47)	4.180*** (9.071)	4.244*** (9.040)	0.213 (3.128)	0.217 (3.124)
<i>Observations</i>	989	989	962	962	990	990	990	990	990	990
<i>R-squared</i>	0.248	0.249	0.220	0.232	0.236	0.294	0.266	0.273	0.146	0.149
<i>Number of Banks</i>	22	22	22	22	22	22	22	22	22	22

Notes: Table reports the panel data fixed effects estimation results. CGF is a time dummy variable that equals one from 2017Q2 and onwards, and zero otherwise. We divide our loan level data into four sub-sample. The first sample (LS1) includes the loans with the lowest amounts and the last sample (LS4) covers the loans with the highest amounts in each period across the banks. Similarly, dependent variables, *npl_LS1* to *npl_LS4*, indicate the non-performing loan ratio of the banks for their commercial loans that is stratified according to loan size. *degree_LS1* to *degree_LS4* show the weighted degree centrality of banks originating from the related loan-size the bank-loan network; i.e., from the sub-samples of LS1 to LS4. To save space, we do not report but all bank-controls and macro-economic variables in Model (4.1) are included in the regressions. Details of the variables are described in Table A2 in the Appendix. Standard errors are shown in parentheses. ***, **, *, indicate the significance level at p=0.01, 0.05, and 0.1, respectively.

degree of foreign banks is insignificant and it decreases the degree of development and investment banks.

Finally, we divide banks into three groups according to their connectedness: strongly connected, moderately connected, and weakly connected banks. Before the implementations of the CGF schemes; i.e. before 2017Q2, we calculate the weighted degree of the banks for each quarter, then grouped them according to the following: The banks with a lower than mean degree of all banks in the related quarter placed in the weakly connected bank group. The remaining banks are divided into two: banks with a lower than mean degree are placed in the moderately connected bank group, and the others are classified in the strongly connected bank group. We keep banks' connectedness group as constant from 2017Q2 and onwards to abstain from the possible endogeneity problems. Table 4.3 shows that CGF schemes have an increasing impact on the bank's connectedness for strongly connected banks, while the impact is insignificant for the moderately and weakly connected banks.

4.5. Empirical Results

In the second chapter we show that there is a significant negative association between banks' portfolio riskiness and their connectedness controlling for the size of the loan portfolio, the liquidity, profitability, and equity of the banks, and even after controlling for the impact of the loan portfolio from multiple borrowings of the firms. Similarly, in this chapter, we investigate whether the CGF schemes change the impact of connectedness on the banks' portfolio riskiness. By the restructuring CGF in 2016, credit guaranteed loan application increased by more than 10-fold in 2017 (CGF, Annual Report 2018). For example, the number of firms applied to CGF scheme increased from 24,066 in 2016 to 311,320 in 2017. In addition to significant change in the borrower portfolio of the banks, loan guarantee schemes may reduce the incentives on banks to screen and monitor the

quality of loans by reducing collateralized loans and making riskier loans. Thus, the revised CGF scheme in Türkiye in 2016 provide us to study whether the publicly supported guarantee schemes increase the loan portfolio riskiness of banks and change the relation between banks' connectedness and loan riskiness.

We use a panel data model to estimate how CGF schemes affect the relation between banks' connectedness emerging from common borrower firms and their overall portfolio riskiness. Our sample extends the period from 2007Q1 to 2018Q1 in a quarterly frequency. As in the second chapter, we estimate the following model employing panel data fixed effects methodology:

$$Y_{it} = \alpha + \beta \text{ degree}_{it} + \Gamma CGF_t + \mu \text{ degree}_{it} CGF_t + \Theta X_{it} + \Psi Z_t + c_i + \epsilon_{it} \quad (4.1)$$

We measure the centrality of the banks with our weighted degree (*degree*) measure as explained in Chapter 2. CGF_t is a time dummy variable indicating the periods when CGF schemes starts and continues to be implemented. Hence, it equals one from 2017Q2 and on-wards, and zero otherwise. $\text{degree}_{it} CGF_t$ is the multiplication of *degree* and CGF_t . X_{it} is a matrix of bank-specific characteristics and Z_t indicates a vector of macroeconomic variables. α is the intercept term, β is the coefficient for weighted degree centrality, γ is the coefficient for CGF schemes, and μ is the coefficient showing how CGF schemes affect the impact of degree on the loan portfolio riskiness of the banks. c_i is the unobserved bank-specific fixed effects and (ϵ_{it}) is the idiosyncratic error term following i.i.d. process with zero mean and variance σ_ϵ^2 .

Bank-specific controls, X_{it} , are the overall granted loan volume of the banks, banks' profitability, liquidity, efficiency, and capital. Macroeconomic control variables, Z_t , are the sovereign risk proxied by the 5-year credit default swap

premium for Türkiye, economic growth measured as the two-period lag of real GDP growth, and monetary policy stance proxied by the weighted average cost of funding of the CBRT. The definition of the variables is explained in Chapter 2 and represented in Table 2.A2 at the end of the chapter.

In line with the second chapter, we stratified the loan-level data into four sub-samples according to the size of the individual commercial loans by banks in order to disentangle the impact of loan size on bank credit risk. The boundaries of the strata are determined by SMEs' asset size boundaries and their average borrowings from banks. Therefore, the inflationary impacts on the limits of the strata are also considered. From each sub-sample, we extract the bank-loan network and compute the weighted degree centrality of the banks.

Moreover, we calculate the non-performing loan ratio of the banks for each stratum separately. The dependent variables are npl_LS1 to npl_LS4 indicating the non-performing loan ratio of the banks for commercial loans that is stratified on their size. The first sample ($LS1$) includes the loans with the lowest amounts and the last sample ($LS4$) covers the loans with the highest amounts in each period across the banks. $degree_LS1$ to $degree_LS4$ show the weighted degree centrality of banks originating from the bank-loan network of the related loan-size sub-samples; i.e., $LS1$ to $LS4$. The first sub-sample ($LS1$) includes the loans with the lowest amounts whereas the last sub-sample ($LS4$) covers the loans with the highest amounts in each period across the banks.

Table 4.4 represents the estimation results for the impacts of CGF schemes on the relation between banks' connectedness and loan portfolio riskiness for the whole sample and across portfolio loan size groups. It is important to note that for all of the estimations, CGF schemes significantly increases the loan portfolio riskiness of the banks. Moreover, the impact of CGF schemes on the relation between the

degree and bank loan riskiness is significantly negative across all sub-samples. It means that CGF schemes supports the decreasing impact of the connectedness of the banks on portfolio riskiness.

As in second chapter, we add two variables to our baseline model (3.1.): *common firms1* is the share of common borrowing firms to other borrowing firms in a bank for each period. *common firms2* is the ratio of the loan volume of the common borrowing firms to the loan volume of the other borrowing firms within each bank for each quarter. As seen in Table 4.5, the impact of loan centrality remains significantly negative schemes for across all sub-samples. Moreover, the impact of CGF schemes support this negative relation.

4.6. Conclusion

Since global financial crisis in 2008/2009, the use of public loan guarantees provided much needed liquidity to small and medium-sized enterprise (SMEs) and non-SMEs in both developed countries and emerging economies (Agnese et al, 2019). Similarly, Treasury support for the guarantee limit by Credit Guarantee Fund of Türkiye was increased 12.5-fold to ease financial constraints for small and medium-sized enterprises and banks started to grant loans exploiting from this new policy. Thus, in this chapter, we examine the impact of the CGF on the connectedness of the banks emerging from their common borrower firms.

We find that the connectedness of the strongly connected banks, or large banks, or state-owned banks are increased with these policies. Moreover, we show that CGF schemes supports the negative relation between the bank connectedness and loan portfolio riskiness. Finally, we document that banks' loan portfolio riskiness

Table 4.5: Estimation Results of the Baseline Model Controlling for Multiple Borrowing

<i>Variables</i>	All		<i>Micro-Size Loans</i>		<i>Small-Size Loans</i>		<i>Medium-Size Loans</i>		<i>Large-Size Loans</i>	
	<i>npl</i>	<i>npl</i>	<i>npl_LS1</i>	<i>npl_LS1</i>	<i>npl_LS2</i>	<i>npl_LS2</i>	<i>npl_LS3</i>	<i>npl_LS3</i>	<i>npl_LS4</i>	<i>npl_LS4</i>
<i>CGF</i>	1.370*** (0.306)	1.367*** (0.301)	16.84*** (1.779)	17.20*** (1.768)	19.84*** (1.396)	20.44*** (1.399)	3.251*** (0.871)	2.971*** (0.872)	1.013*** (0.308)	1.027*** (0.303)
<i>degree</i>	-0.048*** (0.007)	-0.046*** (0.007)								
<i>CGF*degree</i>	-0.002 (0.006)	-0.002 (0.006)								
<i>degree_LS1</i>			-1.208*** (0.399)	-1.258*** (0.402)						
<i>CGF * degree_LS1</i>			-1.544*** (0.393)	-1.530*** (0.393)						
<i>degree_LS2</i>					-0.141* (0.081)	-0.185** (0.081)				
<i>CGF * degree_LS2</i>					-0.773*** (0.086)	-0.767*** (0.087)				
<i>degree_LS3</i>							-0.222*** (0.021)	-0.202*** (0.021)		
<i>CGF * degree_LS3</i>							-0.076*** (0.024)	-0.0761*** (0.024)		

Table 4.5. (continued)

	All		Micro-Size Loans		Small-Size Loans		Medium-Size Loans		Large-Size Loans	
Variables	<i>npl</i>	<i>npl</i>	<i>npl_LS1</i>	<i>npl_LS1</i>	<i>npl_LS2</i>	<i>npl_LS2</i>	<i>npl_LS3</i>	<i>npl_LS3</i>	<i>npl_LS4</i>	<i>npl_LS4</i>
<i>degree_LS4</i>										
-0.040***										-0.040***
(0.006)										(0.006)
<i>CGF * degree_LS4</i>										
<i>common_firms1</i>	0.033		0.447*		0.796***		-0.405***		-0.011**	-0.011**
	(0.040)		(0.264)		(0.196)		(0.117)		(0.005)	(0.005)
<i>common_firms2</i>		0.074***		0.084				0.0377	0.046	0.060***
		(0.015)		(0.127)				(0.046)	(0.040)	(0.016)
<i>Constant</i>	-8.955***	-7.554**	12.22	20.96	-9.857	-55.40***	-61.39***	-1.031		
	(3.186)	(3.098)	(22.46)	(22.42)	(15.66)	(9.177)	(9.058)	(3.186)		
Observations	989	989	962	962	990	990	990	990		990
R-squared	0.249	0.266	0.235	0.233	0.306	0.295	0.282	0.274	0.150	0.162
Number of Banks	22	22	22	22	22	22	22	22	22	22

Notes: Table reports the panel data fixed effects estimation results. The dependent variable *npl* is non-performing ratio of the commercial loans. *degree* is the network centrality of the banks, measured by weighted degree, originating from their lending to common firms. *CGF* is a time dummy variable that equals one from 2017Q2 and onwards, and zero otherwise. We divide our loan level data into four sub-sample. The first sample (*LS1*) includes the loans with the lowest amounts and the last sample (*LS4*) covers the loans with the highest amounts in each period across the banks. Similarly, dependent variables, *npl_LS1* to *npl_LS4*, indicate the non-performing loan ratio of the banks for their commercial loans that is stratified according to loan size. *degree_LS1* to *degree_LS4* show the weighted degree centrality of banks originating from the related loan-size the bank-loan network; i.e., from the sub-samples of *LS1* to *LS4*. *common_firms1* is the ratio of the number of firms borrowing also from other banks to the number of firms borrowing only from the bank itself, *common_firms2* is the ratio calculated by the total amount of the loans that firms borrow also from other banks over the total amount of loans that firms financed only by the bank itself. To save space, we do not report but all bank-controls and macro-economic variables in Model (3.1) are included in the regressions. Details of the variables are described in Table A2 in the Appendix. Standard errors are shown in parentheses. ***, **, * indicate the significance level at $p=0.01$, 0.05 , and 0.1 , respectively.

increases with these schemes. Our findings suggest that the CGF schemes also enhances banks' incentives for lending by supporting their connectedness. However, CGF schemes are found to increase the credit riskiness of the banks. The policy implication of our study is that CGF schemes should be designed by taking into account the individual riskiness of the banks as well as the riskiness of the banking system together.



CHAPTER V

CROSS-BORDER BANK NETWORK

5.1. Introduction

The 2008–2009 global financial crisis demonstrated the role of interconnected banks in transmitting the financial crisis. Despite a number of empirical studies on the impact of the global financial crisis on cross-border bank lending (Cetorelli and Goldberg, 2011; Minoiu and Reyes, 2013; Bruno and Shin, 2015; Cerutti and Claessens, 2017; Amiti et al. 2019), the impact of the crisis on the interconnectedness of the domestic banks through the global financial system has not been studied largely due to a lack of granular data (Abbassi et al., 2022).¹ The interconnectedness of banks may arise directly via transactions between them or indirectly due to common asset holdings.² In this paper, our aim is to study the interconnectedness of the resident banks in an emerging economy that is originated from direct cross-border transaction of banks, and explore whether, and how, bank interconnectedness evolved during and after a local financial shock. To this end, we

¹Most of the existing studies on the role of global banks in transmitting shocks and creating vulnerability utilize the BIS consolidated and locational banking statistics (see e.g., Bruno and Shin, 2015; Cerutti et al., 2015; Cerutti et al., 2017; Cerutti and Claessens, 2017). The data covers cross-border bank claims on other countries' banks, but banking statistics are aggregated across banks and do not provide detailed breakdowns of assets and liabilities, and may fall short in the comprehensive analysis and/or risk surveillance of bank-to-bank interactions. On the other hand, there are a number of studies employing confidential syndicated loan-level data by Dealogic's Loan Analytics database (Hale, 2012; Cerutti et al., 2015; Hale and Obstfeld, 2016; Caballero et al., 2018; Hale et al., 2020)

²See the studies by Hale, 2012; Georg, 2013; and Bluhm and Krahnen, 2014; for direct relations and Allen and Gale, 2000; Nier et al., 2007; Caccioli et al., 2014; and Tasca and Battiston, 2016; for common asset holdings.

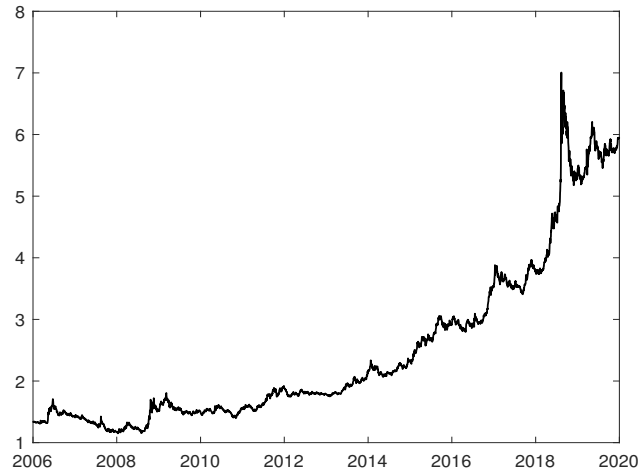


Figure 5.1: Exchange Rate of Turkish Lira Against US Dollar

first construct the cross-border network of banks employing a confidential loan-level data during 2012–2019 in Türkiye. Then we analyze the impact of the exchange rate shock (a rapid depreciation of the local currency) on the foreign currency (FX) borrowings of the resident banks via cross-border network.

Since the implementation of the inflation targeting regime in 2006 until the end of the studied period, Türkiye experienced the largest depreciation in the Turkish lira (TL) during August of 2018 (Figure 5.1). The lira depreciated more than 30 percent in one month and Türkiye’s CDS and bond spreads have risen nearly 160 and 350 basis points, respectively - the highest level seen since the peak of the European debt crisis. Higher refinancing costs put further strain on government budgets and corporate borrowers, i.e., a major risk for the Turkish banking sector. Thus, Türkiye’s lira crisis in 2018 presents a unique laboratory to study the impact of a local shock on the cross-border network of banks in an emerging economy. Moreover, it allows us to investigate whether the impact of FX shock differs among resident banks, lending financial institutions from advanced or emerging economies, and across the regions of cross-border banks’ country origin (see Figure 5.2, for

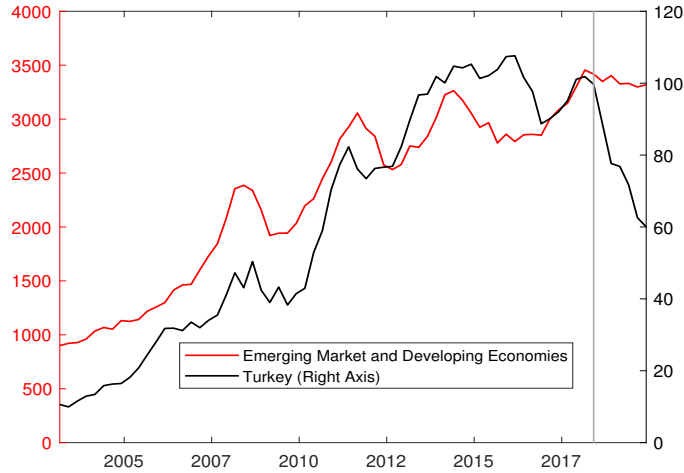


Figure 5.2: BIS Locational Statistics

Figure shows the outstanding volume of FX loans extended to emerging market and developing economies and Türkiye in billion USD. Grey vertical lines show August 2018 when Türkiye experienced a sharp currency depreciation.

example, for how cross-border flows to Türkiye behaved differently compared to other emerging economies after the exchange rate shock in Türkiye).

A number of studies explore the effects of global real and financial shocks on cross-border banking activities, including the impact of 2008-2009 financial crisis, euro debt crisis shock and US monetary policy shocks on the capital flows to advanced and emerging economies (Reinhardt and Riddiough, 2015; Castrén and Rancan, 2014; Albertazzi and Bottero, 2014; Claessens, 2017; Cerutti et al., 2017; Alper et al., 2020; and Abbassi et al., 2022). In contrast, we focus on the impact of a local crisis, a large currency depreciation, on FX borrowings of resident banks from a network perspective.

Spillover effects within the domestic financial system (Upper and Worms, 2002; Degryse and Nguyen, 2004; Sumer and Yildirim, 2019) or across the countries which are connected by global financial system are mainly studied via social network analysis (Brunetti et al., 2019; Zhao et al., 2023). However, due to lack of

data and adequate analysis techniques, the interconnectedness within the global financial system has not been studied extensively at the empirical level.

Nevertheless, the BIS consolidated and locational banking statistics compensate the need of international data as a result of the fact that cross-border financing by banks forms the most important part of non-FDI capital flows or total cross-border debt flows (Cerruti et al., 2017; Bruno and Shin, 2015). Hence, most of the limited number of studies utilize the BIS consolidated and locational banking statistics (McGuire and Tarashev, 2008; Buch et al., 2009; Cetorelli and Goldberg, 2011; Minoiu and Reyes, 2013; Bruno and Shin, 2015; Cerutti and Claessens, 2017; Cerutti and Zhou, 2017). Moreover, there are a number of studies employing confidential syndicated loan-level data by Dealogic’s Loan Analytics database (Hale, 2012; Cerutti et al., 2015; Hale and Obstfeld 2016; Caballero et al., 2018; Hale et al., 2020). Contrary to these two main databases used in the literature, we employ a confidential loan level bank to bank transaction data from the Banking Regulation and Supervision Agency and Central Bank of Turkey. Our database covers all cross-border relations of banks. We compile these data with banks’ balance sheet and income statements data which enable us to focus on the “pull factors” of borrower banks directly rather than that of the borrower countries which may result in erroneous inference.

Hence, we first construct cross-border interbank networks using transaction level data, specifically a bilateral panel of 47 banks in Türkiye with 636 counterparties from 101 source countries, during the period between March 2012 and December 2019. Then, we examine empirically how these networks between domestic banks and global counterparties varied after the exchange rate shock. We show that during and after the FX currency shock, the strength, i.e., size of FX borrowings, of the resident banks in the cross-border network significantly decreased. We also find that weakly connected banks and private commercial banks are the most

negatively affected by the currency shock.

The banking landscape, and cross-border banking in particular, has gone through a process of deep transformation over the past two decades. Recent financial turmoil in the advanced economies –the global financial crisis and the European sovereign debt crisis– resulted in a more fragmented banking landscape, which is characterized by the arrival of new banking groups from other regions, such as Asia (China and India) and the Middle East (Mathieu et al., 2019). Shim and Shin (2021) document that during and after the global financial crisis, financial stress in lender countries (where international banks are headquartered) is a more important driver of banking outflows from emerging market economies than the local financial conditions and macroeconomic fundamentals of emerging economies. Cerutti et al. (2015) show that there is lesser informational asymmetries as economic integration increases and geographical distance between lender and borrower countries decreases. Kempf et al. (2023) suggest that ideological alignment with foreign governments is an important determinant of international capital allocation. Considering international banking trends and Türkiye’s more diversified regional economic engagement in recent years, we also investigate the differences in FX loan transactions of domestic banks with cross-border banks from specific country groupings such as advanced, emerging, and Middle East countries. We further study the cross-border financing by supranational financial institutions, i.e., multilateral development banks (EBRD, EIB, IFC, World Bank Group, etc.) that do not belong to any country grouping, but have played a role in facilitating long-term financial flows in the emerging economies, especially during the post-global financial crisis period (Gurara et al., 2020; Broccolini et al., 2021).

Our paper makes two primary contributions to the cross-border bank lending literature. Our study is the first to investigate the impact of a local currency shock in the cross-border network of domestic banks. We find that currency shock has a

significant and negative impact on cross-border interbank networks and the effect is strongest among weakly connected domestic banks. Second, we study the marginal effect of diversification in lenders' country origin on the impact of the domestic currency shock on FX borrowings. We show that the cross-border borrowing of domestic banks in the case of FX shock does not significantly change if the counterparty banks are headquartered in emerging markets, while it decreases if the counterparty banks are from advanced or Middle East country groups or the counterparty is a supranational institution. In addition, we find that affiliation with foreign counterparties supports the amount of FX borrowings of resident banks in normal times. However, it does not have an accommodating impact in the case of a FX shock, and it has even a decreasing impact if the counterparty is from the Middle East region. Our results imply that diversification in lender banks' country origin contributes to decrease the foreign exchange exposure of domestic banks.

The paper proceeds as follows: In Section 2, we describe our data, explain how we calculate network statistics, and present our empirical strategy. In Section 3, we summarize and interpret our empirical findings on the effect of currency shock on cross-border borrowings. In Section 4, we conclude our paper with a brief discussion and policy implication.

5.2. Data and Methodology

5.2.1 Data

In this study, we use a unique transaction-level dataset from the Central Bank of the Republic of Türkiye (CBRT) and the Banking Regulation and Supervision Agency (BRSA) for the period of March 2012 to December 2019.³ The beginning of the sample period results from data availability and the end of the period is

³The data-set used in this chapter is gathered from Tuba Pelin Sümer who compiled and aggregated data by hand in her doctoral study (Sumer, 2019).

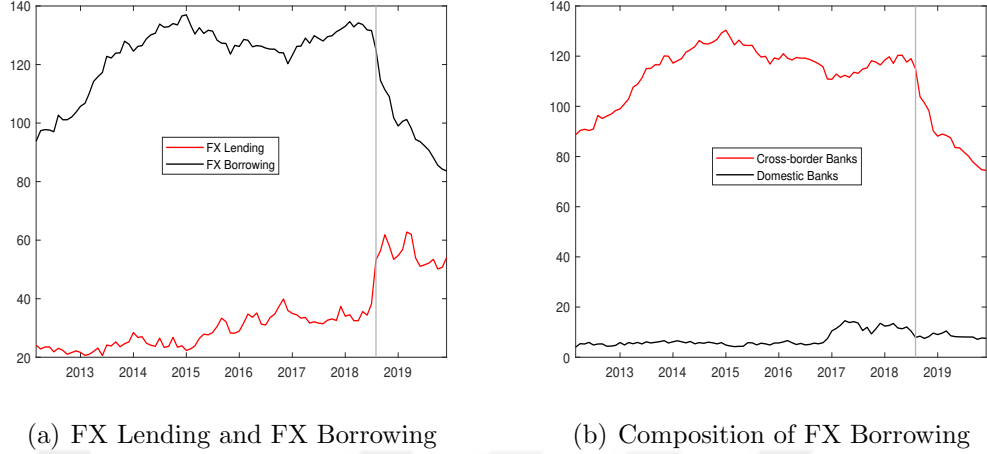


Figure 5.3: FX Lending and FX Borrowing of Banks

Figure (a) shows total amount of FX lending and FX borrowing of resident banks in billion USD. Figure (b) shows composition of FX borrowing of resident banks from cross-border banks and domestic banks in billion USD. Grey vertical lines show August 2018 when Türkiye experienced a sharp currency depreciation.

limited to December 2019 to be able to refrain from the effects of the pandemic.

The data contains the outstanding volume of foreign currency and Turkish lira denominated repo, deposit, and loan type transactions between resident banks and cross-border banks that are reported in a monthly frequency. We define cross-border banks as the banks whose headquarters are outside of Türkiye. In each month, more than one transaction may take place between the same borrower-lender pair. We aggregate all these transactions to obtain one record for the same resident bank-counterparty pair for each period and type of transaction.⁴

We have 47 resident banks in our study whose assets comprise approximately 99 percent of the assets of the Turkish banking sector. As it is shown in Figure 5.3,

⁴In the CBRT-BRSA database system, there is a dataset in which derivative transactions are reported as well. Resident banks use derivative transactions (mainly cross-currency swaps) to hedge currency risk arisen from the original on-balance sheet transactions and carry nearly zero net FX position. During the analysis period (March 2012-December 2019), net FX position of Turkish banks over regulatory capital ranged between -2.2 percent and +4.9 percent with an average of 0.6 percent. Besides the aim of protecting their balance sheets from currency movements, BRSA regulation limiting net FX position over regulatory capital with 20 percent leads on-balance sheet FX position of Turkish banks to be a mirror of off-balance sheet FX position. Hence, we do not cover derivative transactions (off balance sheet items) in our study.

resident banks are net FX borrowers and most of their FX borrowings are from cross-border banks. We use gross cross-border FX borrowings of the resident banks within the network of the banking system. In the literature, there are studies using the net amount of borrowings and receivables (Upper and Worms, 2004; Elsinger et al., 2006; Degryse and Nguyen, 2007). However, more recent evidence shows that analyzing the cross-border banking at a gross and not a net level provides a better understanding of the impacts of the global financial crisis (Borio and Disyatat, 2010; Shin, 2012). Both cross-border lending and depositing have increased dramatically in the past 25 years, each driven by different factors and with different impacts on the financial sector and the global economy. We argue that the total amount of FX borrowings without netting with receivables is critical to incorporate different characteristics inherent in cross-border relations. For example, the share of the FX receivables of Turkish banks from cross-border counterparties in total assets increased from 1.5 percent to 3.4 percent during the period of December 2017 to October 2018 while FX borrowings decreased. The increase in FX receivables was associated with the CDS level, which is a trigger point for margin calls related with FX borrowing (Sümer and Özyıldırım, 2021). This anecdotal evidence shows that if net borrowings (borrowings-receivables) of Turkish banks were used in the analysis, the increase in receivables would hinder the decrease in borrowings of Turkish banks. Hence, we focus on the gross cross-border FX borrowings of resident banks within the network of banking system in Türkiye.⁵

In the dataset, we have different types of financial institutions as counterparties, and we call them “banks” throughout the paper since a larger share of these counterparty institutions are banks. The counterparty financial institutions are

⁵Domestic currency borrowings and foreign and domestic currency receivables are quantitatively very small compared to FX borrowings. During the sample period, while the sum of TL and FX receivables in total assets of Turkish banks from cross-border counterparties range between 0.9 percent and 3.5 percent; TL borrowings range between 0.3 percent and 1.8 percent, which are very small compared to FX borrowings that range between 9.9 percent and 16.4 percent during the analysis period.

reported with their SWIFT codes and names. SWIFT codes enable one to identify counterparties uniquely, but the same counterparty financial institution may be reported with many different names. For the transactions that the SWIFT codes of the counterparties are reported we use SWIFT codes, otherwise, we use names to identify the counterparties. Most cross-border banking groups have fairly complex organizational structures. They run operations through a hybrid structure that includes both branches and subsidiaries. We group branches and subsidiaries of the parent banks under a single parent bank umbrella by hand. For example, there are 24 SWIFT codes belonging to the HSBC group that operates in different countries, and we group all of these banks under the parent bank's name, HSBC Holdings plc.⁶ We count 880 SWIFT codes belonging to 636 different counterparties including domestic banks during the sample period.⁷

Figure 5.4 represents the composition of FX borrowings from cross-border banks by transaction types. While the share of FX loan borrowings over total FX borrowings is on average 74 percent, the share of repo and deposit borrowings are 14 and 12 percent, respectively. The motivations of banks for conducting loan, repo, and deposit transactions are different. While repo transactions are performed mostly for short-term liquidity needs, deposit transactions are exercised mainly for correspondent bank relations. In order to account for changes in long-term relations between resident banks and cross-border banks, we focus on analyzing loan type relations in the empirical section of this paper.

⁶The SWIFT code of EBBK belongs to HSBC Bank Egypt and the SWIFT code of HBMB belongs to HSBC Bank Malaysia which are grouped together under HSBC Holdings plc.

⁷We exclude some of the counterparties from our analysis based on defined criteria. We exclude counterparties with SWIFT codes whose frequency of reporting is less than 100 and whose total size is less than 1.1 billion TL for the seven-year analysis period. The excluded SWIFT codes constitute 0.36 percent in terms of frequency and 0.37 percent in terms of size.

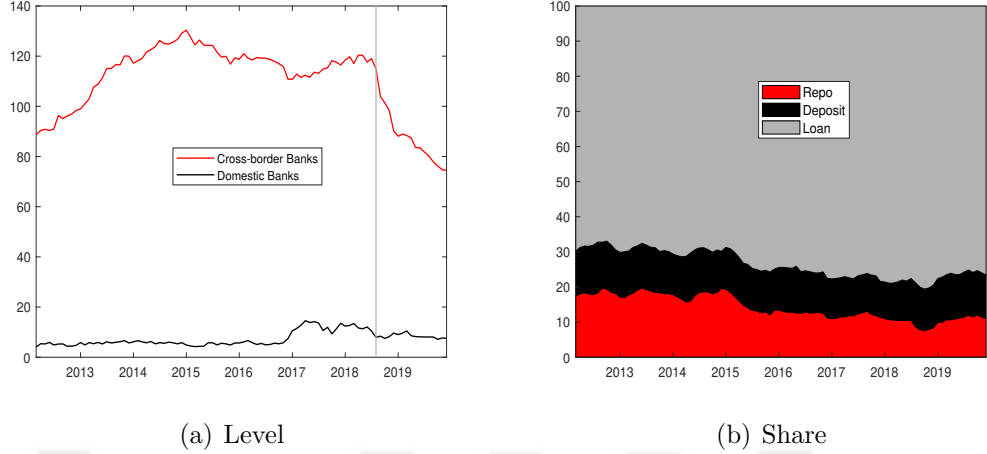


Figure 5.4: Composition of Cross-Border FX Borrowings

Figure (a) shows the instrument composition of FX borrowings of resident banks in billion USD. Figure (b) shows the share of these instruments in total.

5.2.2 Construction of Cross-Border Network

We construct a cross-border network of resident banks in Türkiye using their cross-border transactions. A cross-border network is a bipartite network such that the resident banks and cross-border counterparties belong to two different sets, as borrowers and lenders, respectively. The links (transactions) exist only between these two sets, not within them. As a result, only degree and strength stand out as relevant centrality measures since other measures as betweenness centrality and closeness centrality can not be calculated in bipartite networks. We calculate the degree of the resident banks as the number of cross-border counterparties that they have at least one borrowing or lending relation. On the other hand, we calculate the strength of the resident banks as their total amount of FX loan borrowings from cross-border banks.

Figure 5.5 shows the average degree and strength of banks during the period between March 2012 and December 2019. Cross-border connectedness of banks displays an increasing trend during the period from September 2012 through June

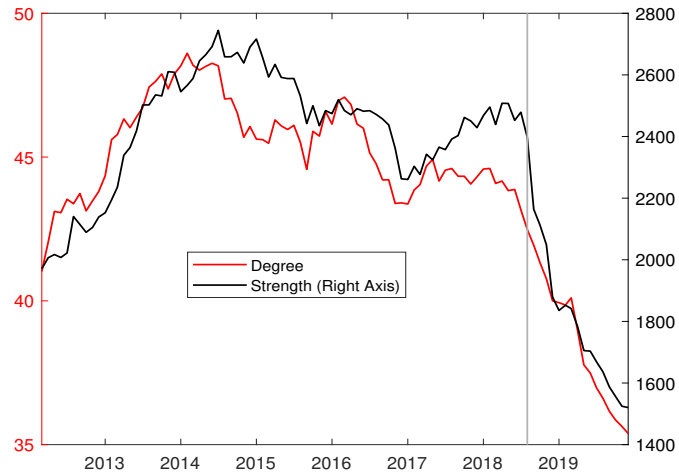


Figure 5.5: Average Strength Centrality and Degree of Banks

Figure shows the average strength and degree measure of resident banks. Degree is the number of counterparties that each resident bank has at least one borrowing or lending relation with, strength is the sum of FX loan borrowings in million USD that each resident bank gathers from its counterparties. Grey vertical line shows August 2018 when Türkiye experienced a sharp currency depreciation.

2014, confirming the cross-border impact of quantitative easing (QE) in the major advanced economies. Later, the existence of uncertainty about the timing of the exit from QE, the weakening global growth momentum, and the decreasing demand in domestic markets followed a slow-down in degree and strength measures of resident banks until the end of 2016. This trend reversed again in 2017, as a result of growing domestic credit and rising risk appetite towards developing countries. Uncertainties generated during the Brexit process, the appreciation of the US dollar arisen from the balance-sheet normalization process in the Fed's monetary policy in October 2017, and increased protectionist tendencies in international trade led to fluctuations in global financial markets during the first half of 2018. Finally, the exchange rate shock in August 2018 significantly reduced the connectedness of resident banks (Figure 5.5).⁸ The cross-border network of the resident banks six

⁸See times series evolution of resident banks' degree centralities in Figure 5.A2 at the end of the chapter.

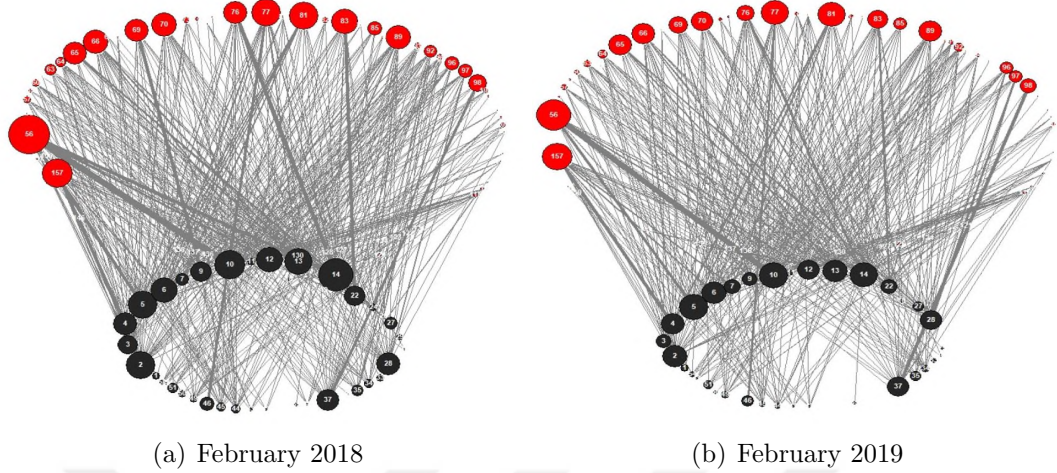


Figure 5.6: Bipartite Cross Border Network of Resident Banks

Figure shows the network of the resident banks six months before and after the FX shock. Black circles show resident banks, and red circles show cross-border countries. Line and circle size becomes thicker as the comparative weight of the relation increases. Network graphs are plotted using Pajek.

months before and six months after the FX shock is represented in Figure 5.6.

Black circles show resident banks and red circles show the countries where the cross-border banks' headquarters are located. As it can be seen in the figure, the nodes of the network (black and red circles) become smaller as the comparative weight of the relation decreases after the currency shock in August 2018.

In the empirical analysis, we use connectedness both as a dependent variable and independent dummy variable indicating banks' cross-border centrality classification. To mitigate the endogeneity concern, we group banks based on their (ex-ante) connectedness using pre-crisis data and keep these groups fixed along the sample period. Because the degree (number of counterparties that each resident bank has) and the strength (total FX cross-border borrowings) are positively correlated, banks' centrality classification is based only on the degree rather than the strength. We divide resident banks into three groups: strongly connected, moderately connected, and weakly connected. For each month, we calculate the degree of the resident banks and then take the averages of their degrees across time

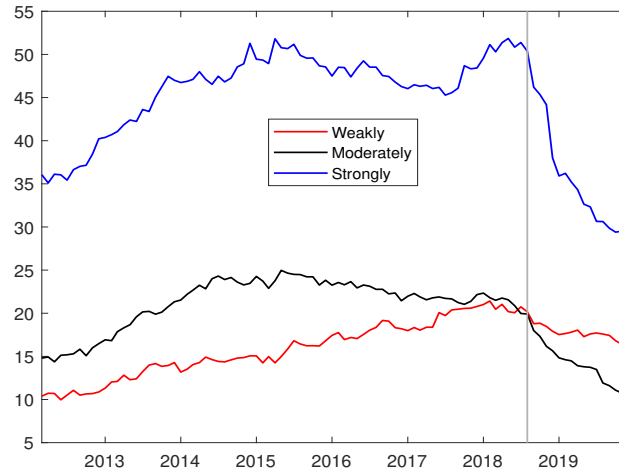


Figure 5.7: Strength Centrality Across Banks' Connectedness Groups

Figure shows the strength of resident banks according to their connectedness classification, which is determined by their ex-ante average degrees, i.e. before FX shock. The strength value in the Figure is in billion USD. Grey vertical lines show August 2018 when Türkiye experienced a sharp currency depreciation.

before August 2018. The banks with a lower than mean degree of all banks were placed in the weakly connected bank group. The remaining banks are divided into two: banks with a lower than mean degree are placed in the moderately connected bank group, and the others are classified in the strongly connected bank group. Thus, there are seven banks in strongly connected banks, three of which are public banks. All strongly connected banks are large banks and hold about 70 percent of the total assets of the banking system. Eleven banks are moderately connected and they hold 18 percent of the total assets of the banking system. There are 29 weakly connected banks having 12 percent of total assets in the banking system.

The heterogeneity in banks' centrality measure provides a quasi-natural laboratory to analyze the role of centrality on the impact of currency shock on FX borrowings. We observe that regardless of the degree distributions, the currency shock has a negative impact on the centrality (Figure 5.7). However, as we present in the empirical findings, strongly and moderately connected banks are negatively affected

by the currency shock but to a lesser extent compared to the weakly connected banks.

5.2.3 Empirical Strategy

In the empirical analysis, we first study the impact of the currency shock on the strength (FX loan borrowings) of resident banks. Consolidating the granular micro-level transaction data on bank-basis (macro-level), we estimate the following regression (Model 1):

$$Strength_{it} = \alpha + \beta FXShock + X'_{it}\mu + \gamma_i + \epsilon_{it}. \quad (5.1)$$

The dependent variable, $Strength_{it}$, shows the network centrality of bank i at time t . It is calculated using FX loan borrowings. X'_{it} denotes for bank specific control variables and γ_i for bank fixed effects. ϵ_{ijt} is the idiosyncratic error term following i.i.d. process with zero mean and variance.

To understand how an exchange rate shock affects the FX loan borrowings of domestic banks, we estimate the following regression using the loan level data (Model 2):

$$L_{ijt} = \alpha + \beta FXShock + X'_{it}\mu + \gamma_i + \theta_j + \zeta_{ij} + \epsilon_{ijt}. \quad (5.2)$$

The dependent variable, L_{ijt} , is the FX loan of bank i from counterparty bank j at time t . X'_{it} denotes for bank specific control variables. γ_i , θ_j and ζ_{ij} show bank, counterparty, and bank-counterparty fixed effects, respectively. ϵ_{ijt} is the idiosyncratic error term following i.i.d. process with zero mean and variance.

In equations (1) and (2), the main variable of the interest is exchange rate shock ($FX Shock$). It is a time dummy variable that equals one from August 2018 and onwards, and zero otherwise. In addition to the time dummy variable, we use end

of month nominal exchange rate between the US dollar and Turkish lira as a continuous variable to explore how cross-border connectedness of the resident banks may have changed during and after the shock. Our results are robust with the FX shock dummy. In addition, we do not consider the possible endogeneity problem emerging from reverse causality because the cross-border loan transactions by banks constitute only a small part of the overall capital flows of Türkiye. The bank specific control variables (X'_{it}) are: size of a bank measured by the natural logarithm of total assets (*Asset Size*), credit risk proxied by non-performing loan ratio (*npl*), capital adequacy ratio (*CAR*), and the natural logarithm of the volume of FX loans granted by resident banks to domestic firms in Türkiye (*FX Loan Size*). We use *FX Loan Size* as a proxy for the demand of resident banks for FX borrowings from cross-border banks. As seen in Figure 5.A1 at the end of the chapter, the growth rate of FX loans to the domestic sector and the growth rate of FX cross-border borrowings move together during the sample period.

5.2.4 Sub-samples

Alongside the connectedness classification (summarized in Section 2.2), we explore the impacts of the currency shock on the cross-border borrowings according to resident banks' business models and counterparty banks' headquarter country groups. First, based on business models, we classify the resident banks as public commercial banks, private commercial banks, and development banks.⁹ During the sample period, we observe that none of the banks changes their business models. Thus, in our sample, there are three public commercial, 33 private commercial and 11 development banks holding 31, 62, and six percent of total assets in the banking sector, respectively. Figure 5.8 shows that the FX shock has a negative impact on the cross-border network across all bank types. Yet, we empirically find that

⁹Investment banks are also included in the development banks group.

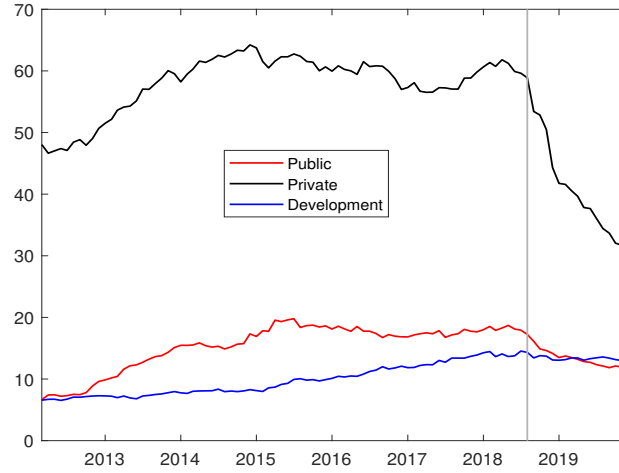


Figure 5.8: Strength Centrality Across Banks' Business Types

Figure shows the strength of the resident banks according to their business types classification. The strength value in the Figure is in billion USD.

private commercial banks are affected most compared to the others.¹⁰

Second, we group counterparty foreign banks based on the country groups of their headquarters. The resident banks borrow mostly from the counterparties whose headquarters are located in the advanced and emerging economies. Furthermore, in line with Türkiye's increased regional engagement recently, Middle East countries appear to be another country classification where resident banks have cross-border borrowing relations.¹¹ Finally, we have the supranational financial institutions group. These multinational development banks (EBRD, EIB, IFC, World Bank Group, etc.) are considered a special case because they play key roles in facilitating long-term financial flows to emerging regions such as Türkiye. The remaining

¹⁰All public commercial banks are strongly connected and none of the development banks are strongly connected.

¹¹The country classification as advanced or emerging economy is based on the criteria by the Bank for International Settlements. On the other hand, in our study we have Middle East classification as well. For this reason, we switch United Arab Emirates, Kuwait, and Saudi Arabia from BIS' classification of emerging economies to our Middle East classification. In our sample, most of the counterparties are headquartered in three advanced economies: United States, United Kingdom, and Japan. Among emerging economies, banks in China and Russia have highest number of counterparty transactions with the resident banks.

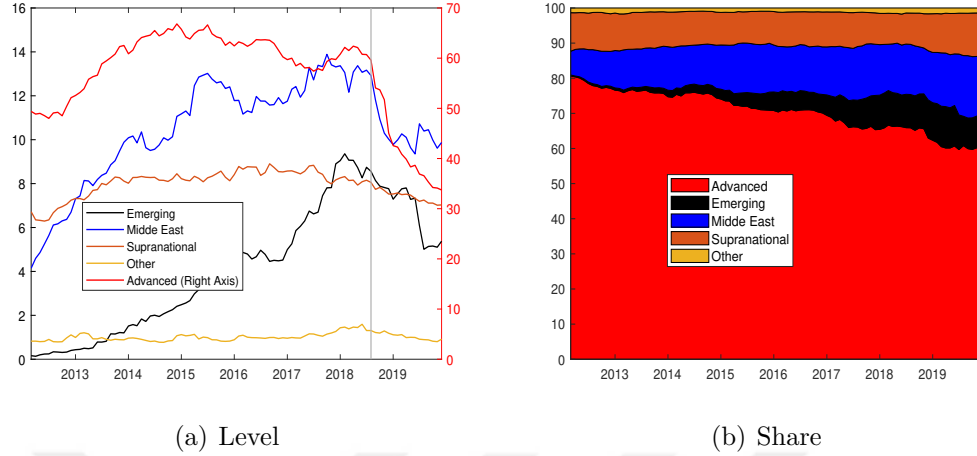


Figure 5.9: FX Loan Borrowings of Resident Banks Across Headquarter Country Grouping of the Counterparty Banks

Figure (a) shows the country group composition of FX borrowings of resident banks in billion USD. Figure (b) shows the share of the FX borrowings by country groupings.

countries are grouped as “others.” As it is seen from Figure 5.9, while the share of advanced economies is highest across the whole sample period, the share is decreases from 78 percent to 59 percent in favor of the shares of the emerging economies and Middle East countries. The share of supranational institutions in total FX borrowings of resident banks are stable during the analysis period. Figure 5.9 shows the negative association between the FX shock and FX borrowings from the cross-border banks across all country groupings.¹²

5.3. Empirical Results

This section presents the empirical results. We start by analyzing the impact of FX shock on the cross-border network of resident banks using macro-level (bank based)

¹²Table 5.A1 and 5A.2 at the end of the chapter document the descriptive statistics and pairwise correlations of the variables that are used in the empirical models before and after the FX shock and across resident banks. The tables show that the degree, FX borrowings, and capital strength of the resident banks decreased after the FX shock. Moreover, the volatility of FX borrowings and credit risk increased. While banks’ FX borrowings from cross-border banks decreased, their FX loans to domestic firms slightly increased. Table 5.A3 and 5A.4 show descriptive statistics based on banks’ business type and connectedness groupings.

data that is presented in Section 3.1. Then, we inquiry the FX exposure of domestic banks to FX shock using micro-level data (loan based) as presented in Section 3.2.

5.3.1 Estimations Using Macro-Level Data

Table 5.1 presents the panel data fixed effects estimation results of Model 1 and shows the effect of exchange rate shock in August 2018 on cross-border connectedness of resident banks.

Table 5.1: The Impact of FX Shock on Banks' Cross-Border Network

	(1)	(2)
<i>FX Shock</i>	-1.012*** (0.080)	-1.925*** (0.404)
<i>Asset Size</i>	0.460*** (0.080)	0.437*** (0.805)
<i>npl</i>	-0.041*** (0.007)	-0.040*** (0.007)
<i>CAR</i>	-0.003*** (0.001)	-0.003*** (0.001)
<i>FX Loan Size</i>	0.457*** (0.061)	0.402*** (0.452)
<i>FX Shock x FX Loan Size</i>		0.068** (0.029)
Bank FE	Yes	Yes
R-squared	0.116	0.117
Number of banks	47	47
Observations	3,920	3,920

Notes: Dependent variable is strength measure of resident banks calculated from FX loan borrowings received from cross-country banks in USD terms. *FX Shock* is a time dummy variable, taking on a value of one for the period during and after the currency shock, i.e., August 2018 to December 2019. *Asset Size* is the natural logarithm of a bank's total assets. *npl* is the non-performing loan ratio of the resident bank. *CAR* is the capital adequacy ratio of the resident bank. *FX Loan Size* is the natural logarithm of a bank's FX loan size in USD terms. *FX Shock x FX Loan Size* is the interaction term that is obtained by the multiplication of *FX Shock* dummy and *FX Loan Size*. Standard errors are shown in parentheses. ***, **, * indicate the significance level at $p=0.01$, 0.05 , and 0.1 , respectively.

We find that exchange rate shock (*FX Shock*) has a significant negative impact on cross-border connectedness, suggesting significant decline in cross-border FX loan

borrowings of the resident banks after the currency shock. We show that cross-border connectedness increases with bank size (*Asset size*) and decreases with credit riskiness (*npl* ratio). The capital adequacy ratio has a negative and significant coefficient. A high level of capital is a means to reduce the risk of solvency, but it does not address the underlying causes that lead to insolvency of a bank. Turkish banks have a capital adequacy ratio that is well above the regulatory limits (e.g., as of December 2019, Turkish banks' average capital adequacy ratio was 18.4 percent), and larger banks, in particular, have smaller CAR. Thus, the negative coefficient for CAR may be implying inefficient and/or risky allocation of resources by the borrower banks. FX lending of domestic banks (*FX Loan Size*) is a proxy for measuring the demand of borrowing from cross-border banks, and as expected, we find that the cross-border network connectedness increases with the demand of resident banks for FX borrowing. In addition, the estimated coefficient of the interaction term *FX Shock* x *FX Loan Size* in column 2 shows that the impact of FX demand on FX borrowing is higher after the exchange rate shock compared to normal times. This suggests that the decrease in FX demand will result in a higher decrease in FX borrowing after the exchange rate shock compared to normal times.

Furthermore, we study the impact of FX shock on cross-border network across banks that are weakly, moderately, or strongly connected as described in Section 5.2.2. Table 5.2 shows that compared to weakly connected banks, FX shock affected strongly and moderately connected banks less negatively.¹³ This finding shows that banks with high cross-border centrality before the FX shock sustained their borrowings after the FX shock, suggesting the importance of diversification for banks to be more resilient to a shock. Similarly, Doerr and Schaz (2021)

¹³The coefficients of *Asset size*, *npl*, *CAR*, and *FX Loan Size* are not reported to save space, but they are robust and available upon request.

Table 5.2: The Impact of FX Shock on Banks' Cross-Border Network Across Banks' Cross-Border Connectedness

	(1)
<i>FX Shock</i>	-1.405*** (0.097)
<i>FX Shock x Strongly Connected Bank</i>	0.871*** (0.188)
<i>FX Shock x Moderately Connected Bank</i>	0.975*** (0.158)
Bank FE	Yes
R-squared	0.127
Number of banks	47
Observations	3,920

*Notes:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard deviations are in parentheses. Dependent variable is strength measure of resident banks calculated from cross-border borrowings in USD terms. *FX Shock* is a time dummy variable, taking on a value of one for the period during and after the currency shock, i.e., August 2018 to December 2019. *FX Shock x Strong Connected Bank* and *FX Shock x Moderately Connected Bank* are interaction terms that are obtained by the multiplication of FX Shock dummy and Strong and Moderate dummies respectively. Strong and Moderate dummies take a value of one if the resident bank is strongly and moderately connected, respectively. The coefficients of natural logarithm of a bank's total assets, non-performing loan ratio, capital adequacy ratio and natural logarithm of a bank's FX loan amount in USD terms are not reported to save space but available upon request.

Table 5.3: The Impact of FX Shock on Banks' Cross Border Network Across Banks' Business Types

	(1)
<i>FX Shock</i>	-1.228*** (0.088)
<i>FX Shock</i> x <i>Public Commercial Bank</i>	0.553** (0.265)
<i>FX Shock</i> x <i>Development Bank</i>	0.958*** (0.167)
Bank FE	Yes
R-squared	0.124
Number of banks	47
Observations	3,920

Notes: Dependent variable is strength measure of resident banks calculated from FX loan borrowings received from cross-country banks in USD terms. *FX Shock* is a time dummy variable, taking on a value of one for the period during and after the currency shock, i.e., August 2018 to December 2019. *FX Shock* x *Public Commercial Bank* and *FX Shock* x *Development Bank* are interaction terms that are obtained by the multiplication of FX Shock dummy and Public and Development dummies, respectively. Public and Development dummies take a value of one if the resident bank is a public bank or development bank, respectively. The coefficients of the natural logarithm of a bank's total assets, non-performing loan ratio, capital adequacy ratio, and natural logarithm of a bank's FX loan amount in USD terms are not reported to save space but available upon request. *p<0. , ** p<0.05, *** p<0.01. Standard deviations are in parentheses.

document that declining financial connectedness makes countries more vulnerable to local financial shocks. In addition, Zhao et al. (2023) show that the greater the syndicated loan network closeness centrality¹⁴ of a country, the more stable the banking industry.

Table 5.3 presents the impact of FX shock on a cross-border network across bank business groups; specifically public commercial banks, private commercial banks, and developments banks. The coefficients on interaction terms suggest that compared to the private banks, the impact of the FX shock is less for both public and development banks. Public commercial banks are different than private and

¹⁴Closeness centrality shows average distance of a country to all countries in the network.

development banks in terms of ease of access to capital. Our findings suggest that cross-country banks may be more willing to support lending to public banks after the exchange rate shock due to Treasury support. Overall, one may also consider the positive interaction term between the FX shock dummy and public bank dummy as another evidence that public banks may play an important role in stabilizing credit flows after a crisis (among several evidence, see for example, Brei and Schclarek, 2015; Coleman and Feler, 2015 for countercyclical support of public banks in times of crisis). Turkish public banks may have used cross-border funds after the exchange rate shock to provide countercyclical support for both public and private sectors. One may expect that development banks are able to borrow from cross-country banks, even during the times of crisis, to extend thematic loans such as financing green investments, supporting women employment, and increasing SME participation besides development facilities as infrastructure projects.

5.3.2 Estimations Using Micro-Level Data

In this section, we investigate the impacts of the FX shock on FX borrowings of the resident banks from one counterparty bank using loan level data. We estimate Model 2 with the panel data fixed effects method. We control for the same bank-specific factors as in the previous macro-level regressions. In addition to bank fixed effects, we have now counterparty fixed effects and multiplication of bank fixed effect and counterparty fixed effect. In this way, we aim to cover the effect of unobserved characteristics originating from the loan transaction itself or the counterparty. Because we use even more granular data, the number of observations are higher in our second set of regressions.

The results in Table 5.4 are consistent with the macro-level (bank-based) regressions. We find that exchange rate shock has a negative and significant impact on cross-border borrowing when bank- and counterparty-specific factors are

Table 5.4: Counterparty Level Estimations: The Impact of FX Shock on Banks' Cross-Border FX Borrowings

	(1)	(2)	(3)
<i>FX Shock</i>	-0.063*** (0.021)	-0.134*** (0.016)	-0.201*** (0.011)
<i>Asset Size</i>	0.350*** (0.023)	0.199*** (0.018)	0.108*** (0.014)
<i>npl</i>	-0.025*** (0.005)	-0.043*** (0.005)	-0.023*** (0.003)
<i>CAR</i>	-0.003*** (0.001)	-0.005*** (0.001)	-0.008*** (0.001)
<i>FX Loan Size</i>	0.041* (0.023)	0.242*** (0.019)	0.256*** (0.017)
Bank FE	Yes		
Counterparty FE		Yes	
Bank FE x Counterparty FE			Yes
R-squared	0.082	0.574	0.813
Number of banks	44	44	44
Observations	87,966	87,960	87,915

Notes: Dependent variable is FX loan borrowing of the resident bank received from the specific cross-country bank in USD terms. *FX Shock* is a time dummy variable, taking on a value of one for the period during and after the currency shock, i.e, August 2018 to December 2019. *Asset Size* is natural logarithm of a bank's total assets. *npl* is non-performing loan ratio of the resident banks, *CAR* is capital adequacy ratio of the resident bank and *FX Loan Size* is natural logarithm of a bank's FX loan amount in USD terms. * p<0.1, ** p<0.05, *** p<0.01. Standard deviations are in parentheses.

accounted. The associations between FX borrowings and other variables (*Asset Size*, *npl*, *CAR*, and *FX Loan Size*) are also consistent with our previous findings.

In Table 5.5, we present empirical results of whether having been affiliated with a foreign bank changes the FX borrowing of resident banks before and after the currency shock. To the best of our knowledge, no previous paper explores the impacts of affiliation on cross-border FX transactions in a local crisis period. Foreign bank entry into emerging market economies has become an important component of financial globalization since the mid-nineties. The global economy

witnessed a massive expansion in banks' international activities, both in the form of larger cross-border credit flows as well as an expansion of foreign subsidiaries and branch networks.

In the literature, a number of papers document that funding shocks to parent banks can be transmitted to their foreign subsidiaries. In particular, country evidence show that home country shocks have a negative effect on lending by subsidiaries in the host country.¹⁵ The paper by Allen et al. (2017) examine host country crises in addition to home country and global crises using a sample of banks in Central and Eastern European (CEE) countries. They find that foreign affiliated banks stabilize lending during domestic crises in CEE countries. Contrary to their study, which represents the effect of having an affiliation with foreign banks on domestic lending, we explore the additional impact of affiliation on the resident banks' direct cross-border transactions in the case of a local currency crisis.

Cerutti et al. (2015) find that the presence of foreign affiliates of the lender country in the borrower country raises both the syndicated and bilateral loan exposures of resident banks. Similarly, we find that affiliation increases the FX borrowings of resident banks in normal times. However, the interaction term between FX shock and affiliation dummy shows that affiliation makes the negative impact of currency shock on the cross-border FX borrowings deeper. In Türkiye, affiliated banks are generally private commercial banks. We argue that unaffiliated public banks and development banks may be driving the result (is shown in Table 5.3) that their cross-border borrowing decreased less after the exchange rate shock.

¹⁵For example, Peek and Rosengren (2000) show that Japanese banks operating in the US reduced lending during the 1990s Japanese crisis. Schnabl (2012) studies the lending behavior of foreign bank affiliates in Peru in the aftermath of the 1998 Russian crisis. Among banks operating in Peru, the ones that borrow internationally, the transmission of liquidity shocks by arm's-length lenders is more than foreign affiliated banks. During 2008-2009, Ceterolli and Goldberg (2012), Aiyar (2012), and Dekle and Lee (2015), document that for the U.S., U.K., and Korea respectively, foreign affiliated banks' lending falls by more than domestic banks' lending.

Table 5.5: The Impact of FX Shock and Affiliated Resident Banks on Banks' Cross-Border FX Borrowings

	(1)	(2)	(3)
<i>FX Shock</i>	-0.067*** (0.020)	-0.134*** (0.015)	-0.191*** (0.012)
<i>Affiliation</i>	2.848*** (0.049)	2.578*** (0.054)	0.275** (0.118)
<i>FX Shock x Affiliation</i>	-0.240*** (0.090)	-0.254*** (0.087)	-0.354*** (0.053)
<i>Size</i>	0.351*** (0.023)	0.198*** (0.017)	0.103** (0.014)
<i>npl</i>	-0.030*** (0.004)	-0.045*** (0.004)	-0.021*** (0.004)
<i>CAR</i>	-0.005*** (0.001)	-0.007*** (0.001)	-0.008*** (0.001)
<i>FX Loan Size</i>	0.023 (0.022)	0.236*** (0.018)	0.259*** (0.017)
Bank FE	Yes		
Counterparty FE		Yes	
Bank FE x Counterparty FE			Yes
R-squared	0.132	0.606	0.813
Number of banks	44	44	44
Observations	87,966	87,960	87,915

Notes: Dependent variable is FX loan borrowing of the resident bank received from the specific cross-country bank in USD terms. *FX Shock* is a time dummy variable, taking on a value of one for the period during and after the currency shock, i.e., August 2018 to December 2019. *Affiliation* is a dummy variable taking a value of one if the resident bank is affiliated with the counterparty foreign bank. *FX Shock x Affiliation* is the interaction term by the multiplication of FX Shock dummy and Affiliation dummy. The coefficients of the natural logarithm of a bank's total assets, non-performing loan ratio, capital adequacy ratio, and natural logarithm of a bank's FX loan amount in USD terms are not reported to save space but available upon request. * p<0.1, ** p<0.05, *** p<0.01. Standard deviations are in parentheses.

Table 5.6 reveals the empirical results that we examine the impact of FX shock on cross-border borrowings across the country groupings where counterparty banks' headquarters are located. We classify the headquarters' countries into five groups. The *Advanced* and *Emerging* country groupings are based on BIS country classification. We have a *Middle East* group that includes the countries where counterparty banks are headquartered in the Middle East region. We have a fourth classification composed of no-nation counterparties, i.e., supranationals (*Supranational*). Finally, the remaining countries are classified in the *Other* grouping. The estimation results in columns (1) to (3) show that the impact of FX shock on FX cross-border borrowings of resident banks from different country groups are robust to the addition of the affiliation relation between the resident and cross-border bank.

We find that the impact of the exchange rate shock varies across countries where counterparty banks are headquartered. First, cross-border FX borrowings of the resident banks decrease with the FX shock if the counterparty's country origin is from advanced economies and the resident banks do not have affiliation with them. On the other hand, if there is an affiliation, then the amount of borrowing from advanced economies does not significantly change with the FX shock. Second, FX shock does not have a significant impact on the cross-border FX borrowings if the counterparty's headquarter is located in emerging economies, regardless of the affiliation relation between the resident and cross-border banks. Though affiliation has an increasing impact on cross-border borrowings from emerging economies before the FX shock, the increasing impact does not change with the FX shock. Similarly, before the FX shock, affiliation has a significant positive impact on FX borrowings if the counterparty headquarter is from the Middle East Group. On the other hand, for this country group, FX shock does not have a significant impact on unaffiliated FX borrowing, the affiliation has a decreasing impact on FX borrowing

Table 5.6: The Impact of FX Shock, Affiliation and Counterparty Bank's Headquarter Country Group on Banks' Cross-Border FX Borrowings

	(1)	(2)	(3)
<i>FX Shock</i> x <i>Advanced</i>	-0.307*** (0.045)	-0.309*** (0.044)	-0.304*** (0.045)
<i>FX Shock</i> x <i>Emerging</i>	0.220 (0.232)	0.265 (0.230)	0.265 (0.253)
<i>FX Shock</i> x <i>MiddleEast</i>	-0.010 (0.072)	-0.021 (0.072)	0.019 (0.072)
<i>FX Shock</i> x <i>Supranational</i>	-0.479*** (0.104)	-0.471*** (0.104)	-0.488*** (0.109)
<i>FX Shock</i> x <i>Other</i>	0.013 (0.076)	-0.009 (0.075)	0.029 (0.073)
<i>Affiliation</i> x <i>Advanced</i>		0.407 (0.591)	0.409 (0.592)
<i>Affiliation</i> x <i>Emerging</i>		3.757*** (0.201)	3.766*** (0.263)
<i>Affiliation</i> x <i>MiddleEast</i>		2.587*** (0.638)	3.195*** (0.930)
<i>Affiliation</i> x <i>Supranational</i>		-0.400 (0.522)	-0.488 (0.526)
<i>FX Shock</i> x <i>Affiliation</i> x <i>Advanced</i>			-0.340 (0.219)
<i>FX Shock</i> x <i>Affiliation</i> x <i>Emerging</i>			-0.005 (0.317)
<i>FX Shock</i> x <i>Affiliation</i> x <i>MiddleEast</i>			-0.805* (0.392)
<i>FX Shock</i> x <i>Affiliation</i> x <i>Supranational</i>			0.302 (0.199)
<i>FX Shock</i> x <i>Affiliation</i> x <i>Other</i>			-1.879*** (0.140)
<i>N</i>	87.966	87.966	87.966
<i>R-squared</i>	0.0183	0.0432	0.0431
<i>Bank</i> x <i>Counterparty FE</i>	Yes	Yes	Yes

Notes: Dependent variable is FX borrowing of the resident bank received from the specific cross-country bank in USD terms. *FX Shock* is a time dummy variable, taking on a value of one for the period during and after the currency shock, i.e., August 2018 to December 2019. *Affiliation* is a dummy variable taking a value of one if the resident bank is affiliated with the counterparty foreign bank. *FX Shock* x *Affiliation* is the interaction term by the multiplication of FX Shock dummy and Affiliation dummy. Before FX Shock, there is not enough observations for affiliated banks borrowing from counterparties whose headquarters are located in the other country grouping. The coefficients of the natural logarithm of a bank's total assets, on-performing loan ratio, capital adequacy ratio, and natural logarithm of a bank's FX loan amount in USD terms are not reported to save space but available upon request.

of resident banks with the FX shock. Finally, the impacts of FX shock and affiliation in the case that resident banks borrow from the supranationals are similar to those when they borrow from advanced countries.

De Haas and van Horen (2013) highlight that international banks did not cut cross-border lending in an unsystematic manner. They show that international banks prefer to lend more to countries that are geographically close to them during a financial crisis. On the contrary, our regression results show that geographical proximity may not result in a similar behavior in emerging economies. They do not significantly cut their lending compared to advanced countries (Europe) that are much closer to Türkiye. Moreover, Papaioannou (2008) shows that institutional, geographical, and historical relations matter in cross-border bank relations. Our regression results show that before currency shock, affiliation has an improving effect if the counterparty's headquarters are located in emerging economies or the Middle East region. But, after the shock, this effect does not change if it is in emerging economies and becomes aggravated if it is from the Middle East region. Thus, we may argue that institutional or historical relations are more important than geographical relations for Türkiye.

5.4. Conclusion

Despite researchers' growing interest in studying interbank transactions using network theory, there are still many interesting questions that have not been explored in the banking literature due to data limitations, including cross-border linkages in the financial system. Recent evidence has shown that monitoring cross-border risks at the bank level carries important information for risk analysis, especially in emerging economies. In this paper, we construct a cross-border bank network in Türkiye and examine the interconnectedness of the resident banks using a very rich and unique dataset during 2012-2019. Furthermore, we focus on a

period surrounding the abrupt depreciation of the local currency in August 2018, which has caused a sharp slowdown in foreign currency cross-border bank flows to Türkiye since the global crisis; the only country to have done so among emerging markets. In particular, we analyze how a large depreciation of local currency alters the existing bank interconnectedness and the amount of FX borrowing of resident banks in an emerging economy.

Our bank level empirical analysis shows that currency shock has a significant and negative impact on cross-border interbank networks. The impact of FX shock on cross-border borrowing is strongest among weakly connected banks. Moreover, private commercial banks are affected more from FX shock compared to public banks and development banks. Our study shows the importance of diversification of cross-border relations from the borrowers' point of view. We find that, in case of FX shock, FX borrowing of domestic banks does not significantly change if the counterparty banks originate from emerging markets, while it decreases if it is from advanced country grouping or the counterparty is a supranational institution. On the other hand, while affiliation supports the FX borrowing of resident banks in normal times on average, it does not sustain its accommodating role on the cross-border borrowing in case of FX shock, and it even worsens the impact of the shock if the lender's nationality is of the Middle East region.

In sum, our results suggest that diversification in lenders even at the regional level implies lower financing risk for borrower banks. To some extent, greater cross-border centrality also represents borrowing from more diverse locations (Zhoa, 2023). With the diversification, resident banks can mitigate the impact of a FX shock as having more financing channels (Levine et al., 2021). From a policy perspective, our findings indicate that diversified domestic banks have a more stable source of funding.

Table 5.A1: Pairwise Correlations

	Before FX Shock				
	(1)	(2)	(3)	(4)	(5)
(1) <i>FX Borrowings</i>	1				
(2) <i>Asset Size</i>	0.705	1			
(3) <i>npl</i>	-0.346	-0.156	1		
(4) <i>CAR</i>	-0.283	-0.409	0.099	1	
(5) <i>FX Loan Size</i>	0.766	0.929	-0.315	-0.427	
	After FX Shock				
	(1)	(2)	(3)	(4)	(5)
(1) <i>FX Borrowings</i>	1				
(2) <i>Asset Size</i>	0.649	1			
(3) <i>npl</i>	-0.227	-0.168	1		
(4) <i>CAR</i>	-0.354	-0.568	-0.073	1	
(5) <i>FX Loan Size</i>	0.698	0.947	-0.239	-0.614	1

Table 5.A2: Descriptive Statistics Before and After FX Shock

	Before FX Shock				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	3,182	50.23	50.54	1.00	236.00
<i>FX Borrowings</i>	3,182	12.06	4.52	0.00	16.19
<i>Asset Size</i>	3,182	16.31	2.00	11.02	20.06
<i>npl</i>	3,182	3.68	6.65	0.00	74.67
<i>CAR</i>	3,182	25.14	31.93	10.05	595.37
<i>FX Loan Size</i>	3,182	13.33	2.39	4.82	17.01
	After FX Shock				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	738	42.85	42.74	1.00	184.00
<i>FX Borrowings</i>	738	11.47	4.77	0.00	16.11
<i>Asset Size</i>	738	16.91	2.02	11.95	20.29
<i>npl</i>	738	5.53	7.64	0.00	70.11
<i>CAR</i>	738	23.37	14.01	12.17	94.07
<i>FX Loan Size</i>	738	13.63	2.29	3.84	16.97

Notes: *FX Borrowings* and *FX Loan Size* are natural logarithm of FX loan borrowings and FX loans of resident banks in USD terms, respectively. *Asset Size* is natural logarithm of total assets, *npl* is non-performing loan ratio, and *CAR* is capital adequacy ratio. *Degree* shows total number of counterparties that resident banks have at least one lending/borrowing relation.

Table 5.A3: Descriptive Statistics Based on Banks' Business Types

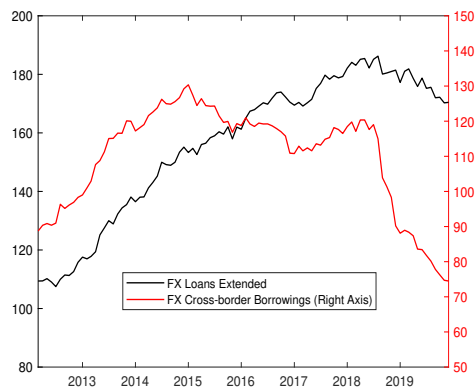
	Public Commercial Banks				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	282	114.87	21.52	64.00	159.00
<i>FX Borrowings</i>	282	15.32	0.53	12.97	15.90
<i>Asset Size</i>	282	19.25	0.50	18.36	20.29
<i>npl</i>	282	3.04	0.95	1.36	5.61
<i>CAR</i>	282	14.93	1.43	12.85	19.01
<i>FX Loan Size</i>	282	16.35	0.36	15.10	16.91
	Development Banks				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	803	17.31	17.79	1.00	71.00
<i>FX Borrowings</i>	803	12.54	2.14	7.79	15.63
<i>Asset Size</i>	803	15.33	1.71	11.02	18.91
<i>npl</i>	803	1.97	3.31	0.00	23.04
<i>CAR</i>	803	32.21	27.04	12.04	271.90
<i>FX Loan Size</i>	803	12.62	2.32	7.32	16.92
	Private Commercial Banks				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	2,835	51.20	49.97	1.00	236.00
<i>FX Borrowings</i>	2,835	11.45	5.11	0.00	16.19
<i>Asset Size</i>	2,835	16.45	1.91	11.18	19.99
<i>npl</i>	2,835	4.71	7.78	0.00	74.67
<i>CAR</i>	2,835	23.69	31.02	10.05	595.37
<i>FX Loan Size</i>	2,835	13.31	2.29	3.84	17.01

Notes: *FX Borrowings* and *FX Loan Size* are natural logarithm of FX loan borrowings and FX loans of resident banks in USD terms and *Asset Size* is natural logarithm of total assets.

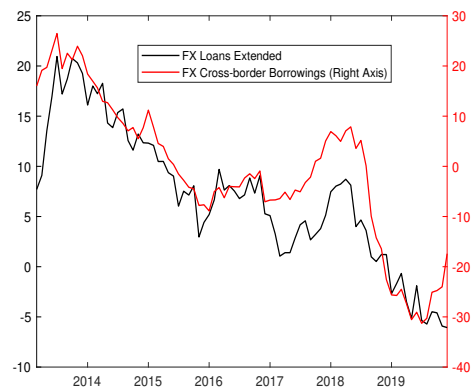
Table 5.A4: Descriptive Statistics Based on Banks' Connectedness

	Strongly Connected Banks				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	2,228	17.41	14.16	1.00	61.00
<i>FX Borrowings</i>	2,228	10.18	4.99	0.00	15.63
<i>Asset Size</i>	2,228	15.25	1.61	11.02	18.91
<i>npl</i>	2,228	4.31	9.00	0.00	74.67
<i>CAR</i>	2,228	31.81	37.48	10.05	595.37
<i>FX Loan Size</i>	2,228	12.21	2.24	3.84	16.92
	Moderately Connected Banks				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	1,034	57.98	14.31	26.00	94.00
<i>FX Borrowings</i>	1,034	13.47	2.84	0.00	15.64
<i>Asset Size</i>	1,034	17.14	1.03	14.58	19.08
<i>npl</i>	1,034	4.05	1.87	0.58	12.73
<i>CAR</i>	1,034	15.63	2.61	11.39	27.26
<i>FX Loan Size</i>	1,034	13.91	1.02	10.70	15.60
	Weakly Connected Banks				
	Obs	Mean	Std. Dev.	Min	Max
<i>Degree</i>	658	140.87	38.71	64.00	236.00
<i>FX Borrowings</i>	658	15.58	0.46	12.97	16.19
<i>Asset Size</i>	658	19.29	0.42	18.36	20.29
<i>npl</i>	658	3.06	1.20	1.16	7.44
<i>CAR</i>	658	15.53	1.60	12.85	21.01
<i>FX Loan Size</i>	658	16.53	0.32	15.10	17.01

Notes: *FX Borrowings* and *FX Loan Size* are natural logarithm of FX loan borrowings and FX loans of resident banks in USD terms and *Asset Size* is natural logarithm of total assets.



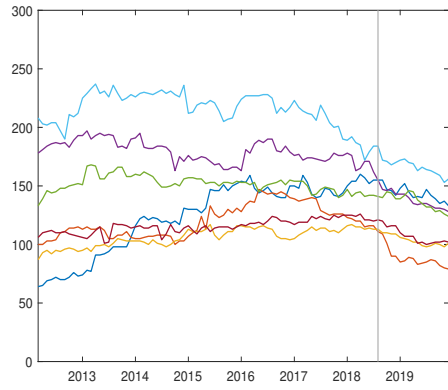
(a) Level



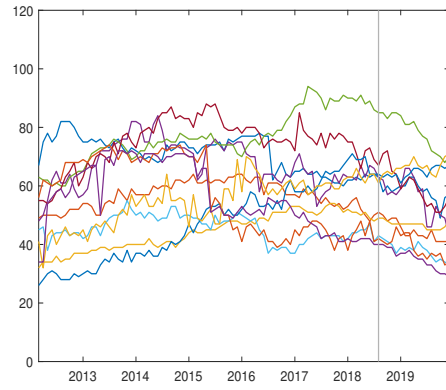
(b) Growth

Figure 5.A1: The Relation Between FX Loans Extended by Resident Banks to Domestic Firms and FX Cross-border Borrowings

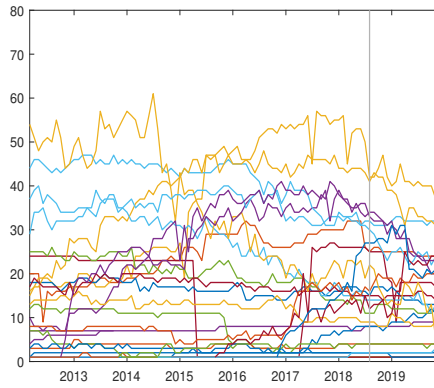
Figure (a) shows the outstanding volume of FX loans extended and FX loan borrowings of the resident banks in billion USD. Figure (b) shows the year-to-year growths of those; respectively.



(a) Strongly



(b) Moderately



(c) Weakly

Figure 5.A2: Degree Centrality Across Banks' Connectedness Groupings

Time series evolution of degree centrality of each resident bank is shown in the Figure. Degree centrality shows total number of counterparties that resident banks have at least one lending/borrowing relation.

CHAPTER VI

CONCLUSION

In this dissertation, we study the networks in banks in Türkiye to investigate the impacts of connectedness of banks on their portfolio riskiness and their FX borrowings from cross-border banks. The motivation stems from two important developments in Turkish banking system during the period between 2007 and 2019. First, Treasury-supported Credit Guarantee Fund (CGF) guarantee limit increased to 12.5-fold at the end of the first quarter of 2017, one of the largest of its kind among the OECD countries (OECD, 2019). Second, the Turkish economy and banking system was hit by the largest depreciation in the Turkish lira in the third quarter of 2018. During the period of following six quarters, a net capital outflow occurred which amounted to 1.9% of GDP. In this dissertation, we investigate the impacts of the former on the bank loan network, while the impact of the latter on the cross-border network.

In the first study, we use our novel connectedness measure that addresses heterogeneous multiple borrowing loan structure among banks. Using confidential data from over 44 million commercial loans from Turkish banks during 2007–2016, we construct a bank network that emerges from the banks’ lending to common firms. While the related literature mostly focuses on systemic risk, our framework allows us to empirically study banks’ loan portfolio riskiness. First, we document that banks’ portfolio riskiness decreases with connectedness, even when controlling for the impacts of loan size and multiple borrowing. Second, we find that the

probability of loan default is higher for highly connected banks compared to weakly connected ones. These findings suggest that highly centralized banks seem to manage their overall portfolio risk better.

In the following chapter, we focus on CGF schemes. We first study the investors' reactions to CGF supports which affected the credit market predominantly. We investigate whether investor reactions to the unprecedented of the increase in Treasury support in CGF are in line with the stated aim of the program. We find that investors anticipated the benefits from public guarantees would outweigh the costs. The positive and significant cumulative abnormal returns (CARs) suggest that the information released in the announcement, in line with the program aims, positively affected investor expectations.

In the fourth chapter of the dissertation, we document the impact of the CGF guarantees on the bank-loan network and bank portfolio riskiness. As mentioned before, treasury-supported funds allocated to these programs were exceptionally large and its impact on the banking industry was exceptional. We show that CGF schemes affected the connectedness of banks differently. While CGF schemes significantly increases the connectedness of large banks and small banks, they do not have a significant impact on mid-size banks. In addition, we find that the connectedness of state-owned banks and private domestic banks significantly increased with the CGF schemes. Moreover, CGF schemes increased the centrality of the strongly connected banks, while they do not have a significant impact on the others. Finally, we find that the CGF schemes supports the decreasing impact of the connectedness of the banks on the bank loan portfolio, though the schemes increase the loan portfolio riskiness of the banks.

In the last chapter, we focus on the impact of currency crisis on cross-border bank network. Using granular data from the Turkish banking system, we exploit a large

currency depreciation in 2018 as a natural experiment to explore whether, and how, bank interconnectedness evolved after the exchange rate shock. Our bank level empirical findings show that currency shock has a significant and negative impact on cross-border interbank networks. The shock has strongest effect on the weakly connected banks as well as private commercial banks. The loan level empirical estimations show that affiliated foreign counterparties that support the amount of FX borrowings in normal times, do not accommodate the impact after the shock. Finally, we find that the impact of the exchange rate shock on cross-border borrowing changes based on lender banks' country origin, showing the importance of diversification of funding partners.

This dissertation contributes to the literature on bank networks; specifically, bipartite loan network of common borrower firms and cross-border loan networks. We hope that our study sheds light on for further studies related with banks' connectedness of common borrowers and cross-border relations.

REFERENCES

- Abbassi, P., Bräuning, F., Fecht, F., & Peydró, J. L. (2022). Cross-border inter-bank liquidity, crises, and monetary policy. *Journal of International Economics* 139, 103657.
- Abbassi, P., Brownlees, C., Hans, C., & Podlich, N. (2017). Credit risk interconnectedness: What does the market really know? *Journal of Financial Stability* 29, 1-12.
- Acharya, V.V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability* 5, 224-255.
- Agnese, P., Rizzo, M., & Vento, G. A. (2019). The impact of Credit Guarantee Schemes on SMEs bankruptcies: an international overview. *Journal of Applied Finance and Banking* 9(4), 1-9.
- Afonso, A., & Sousa, R. M. (2011). What are the effects of fiscal policy on asset markets? *Economic Modelling* 28(4), 1871-1890.
- Aiyar, S. (2012). From Financial Crisis to Great Recession: The Role of Globalized Banks. *American Economic Review* 102, 225-230.
- Akçigit, U., Seven, Ü., Yarba, I., & Yilmaz, F. (2021). Firm-level impact of credit guarantees: Evidence from Turkish credit guarantee fund (No. 21/10). TCMB, Working Paper.
- Albertazzi, U. & Bottero, M. (2014). Foreign bank lending: evidence from the global financial crisis. *Journal of International Economics* 92, S22-S35.
- Allen, F. & Gale, D. (2000). Financial contagion. *Journal of Political Economy* 108, 1-33.
- Allen, F., Jackowicz, K., Kowalewski, O., & Kozłowski, L. (2017). Bank lending, crises, and changing ownership structure in Central and Eastern European countries. *Journal of Corporate Finance* 42, 494-515.
- Allen, F., and Babus, A. (2009). Networks in finance. The network challenge: strategy, profit, and risk in an interlinked world, 367.
- Allen, F., Babus, A., & Carletti, E. (2012). Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics* 104, 519-534.

Alper, K., Altunok, F., Çapacıoğlu, T., & Ongena, S. (2020). The effect of unconventional monetary policy on cross-border bank loans: Evidence from an emerging market. *European Economic Review* 127, 103426.

Amiti, M., McGuire, P., & Weinstein, D.E. (2019). International bank flows and the global financial cycle. *IMF Economic Review* 67, 61-108.

Anadolu Ajansı (2016, December 8). Ekonomi Koordinasyon Kurulunda alınan kararlar açıklandı. Retrieved February 27, 2023, from <https://www.aa.com.tr/tr/gunun-basliklari/ekonomi-koordinasyon-kurulunda-alinan-kararlar-aciklandi/702125#>

Arslan, H. B., & Simsir, S. A. (2016). Measuring takeover premiums in cross-border mergers and acquisitions: Insights from Türkiye. *Emerging Markets Finance and Trade* 52(1), 188–203.

Belaid, F., Boussaada, R., & Belguith, H. (2017). Bank-firm relationship and credit risk: An analysis on Tunisian firms. *Research in International Business and Finance*, 42, 532-543.

Battiston, S., Puliga, M., Kaushik, R., Tasca, P. & Caldarelli, G. (2012). Debtrank: Too central to fail? Financial networks, the FED and systemic risk. Scientific reports, 2, Article No 541.

Beck, T., Klapper, L. F., & Mendoza, J. C. (2010). The typology of partial credit guarantee funds around the world. *Journal of Financial Stability* 6(1), 10–25.

Belo, F., & Yu, J. (2013). Government investment and the stock market. *Journal of Monetary Economics* 60(3), 325–339.

Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market’s reaction to Federal Reserve policy? *The Journal of Finance* 60(3), 1221–1257.

Bertoni, F., Colombo, M. G., & Quas, A. (2018). The effects of EU-funded guarantee instruments of the performance of small and medium enterprises: Evidence from France (No. 2018/52). EIF Working Paper.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *The American Economic Review*, 75(4), 850-855.

Biswas, S.S. & Gómez, F. (2018). Contagion through common borrowers. *Journal of Financial Stability*, 39, 125-132.

Bluhm, M. & Krahnen, J. P. (2014). Systemic risk in an interconnected banking system with endogenous asset markets. *Journal of Financial Stability* 13, 75-94.

- Bonfim, D. (2009). Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking & Finance* 33(2), 281-299.
- Boot, A. W., Thakor, A. V., & Udell, G. F. (1991). Secured lending and default risk: equilibrium analysis, policy implications and empirical results. *The Economic Journal* 101(406), 458-472.
- Borio, C. & Disyatat, P. (2010). Global imbalances and the financial crisis: Reassessing the role of international finance. *Asian Economic Policy Review* 5(2), 198-216.
- Brei, M. & Schclarek, A. (2015). A theoretical model of bank lending: Does ownership matter in times of crisis?. *Journal of Banking & Finance* 50, 298-307.
- Broccolini, C., Lotti, G., Maffioli, A., Presbitero, A. F., & Stucchi, R. (2021). Mobilization effects of multilateral development banks. *The World Bank Economic Review* 35(2), 521-543.
- Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics* 14(1), 3-31.
- Bruno, V. & Shin, H. S. (2015). Cross-border banking and global liquidity. *The Review of Economic Studies* 82, 535-564.
- Bunn, P. & Redwood, V. (2003). Company accounts-based modelling of business failures and the implications for financial stability. Bank of England. Working papers No. 210.
- Caballero, R. J., & Simsek, A. (2013). Fire sales in a model of complexity. *The Journal of Finance* 68, 2549-2587.
- Caballero, J., Candelaria, C., & Hale, G. (2018). Bank linkages and international trade. *Journal of International Economics* 115, 30-47.
- Cai, J., Eidam, F., Saunders, A., & Steffen, S. (2018). Syndication, interconnectedness, and systemic risk. *Journal of Financial Stability* 34, 105-120.
- Caccioli, F., Shrestha, M., Moore, C., & Farmer, J. D. (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking & Finance* 46, 233-245.
- Carletti, E., Cerasi, V. & Daltung, S. (2007). Multiple-bank lending: Diversification and free-riding in monitoring. *Journal of Financial Intermediation* 16, 425-451.
- Castrén, O. & Rancan, M. (2014). Macro-Networks: An application to euro area

financial accounts. *Journal of Banking & Finance* 46, 43-58.

Central Bank of the Republic of Türkiye. (n.d.-a). Bank Loans Tendency Survey. Metadata. <https://evds2.tcmb.gov.tr/index.php?/evds/searchEvdsValue/QHRLbmRlbnN5QA==>

Central Bank of the Republic of Türkiye. (n.d.-b). EVDS: Bank Loans Tendency Survey. <https://evds2.tcmb.gov.tr/index.php?/evds/searchEvdsValue/QHRLbmRlbnN5QA==>

FACTIVA. (2019). Global news database & licensed content. <http://www.factiva.com/>

Cerutti, E. & Claessens, S. (2017). The great cross-border bank deleveraging: supply constraints and intra-group frictions. *Review of Finance* 21, 201-236.

Cerutti, M. E., Claessens, M. S., & Ratnovski, M. L. (2017). Global liquidity and drivers of cross-border bank flows. *Economic Policy* 32, Issue 89, 81-125.

Cerutti, E., Hale, G., & Minoiu, C. (2015). Financial crises and the composition of cross-border lending. *Journal of International Money and Finance* 52, 60-81.

Cetorelli, N. & Goldberg, L. S. (2011). Global banks and international shock transmission: Evidence from the crisis. *IMF Economic Review* 59, 41-76.

Cetorelli, N. & Goldberg, L. S. (2012). Banking Globalization and Monetary Transmission. *Journal of Finance* 67, 1811-1843.

Claessens, S. (2017). Global banking: Recent developments and insights from research. *Review of Finance* 21(4), 1513-1555.

Coleman, N. & Feler, L. (2015). Bank ownership, lending, and local economic performance during the 2008–2009 financial crisis. *Journal of Monetary Economics* 71, 50-66.

Cornett, M., Tanyeri, B., & Tehranian, H. (2011). The effect of merger anticipation on bidder and target firm announcement period returns. *Journal of Corporate Finance* 17(3), 595–611.

Croce, M. M., Kung, H., Nguyen, T. T., & Schmid, L. (2012). Fiscal policies and asset prices. *The Review of Financial Studies* 25(9), 2635–2672.

De Haas, R. & Van Lelyveld, I. (2006). Foreign banks and credit stability in Central and Eastern Europe. A panel data analysis. *Journal of Banking & Finance* 30(7), 1927-1952.

- De Masi, G., Fujiwara, Y., Gallegati, M., Greenwald, B. & Stiglitz, J.E. (2011). An analysis of the Japanese credit network. *Evolutionary and Institutional Economics Review* 7(2), 209-232.
- Degryse, H. & Nguyen, G. (2007). Interbank exposures: An empirical examination of systemic risk in the Belgian banking system. *International Journal of Central Banking* 3, 123–171.
- Dekle, R. & Lee, M. (2015). Do foreign bank affiliates cut their lending more than the domestic banks in a financial crisis? *Journal of International Money and Finance* 50, 16-32.
- Demirguc-Kunt, A., Feyen, E., & Levine, R. (2011). Optimal Financial Structures and Development: The evolving importance of banks and markets. World Bank, mimeo.
- Detragiache, E., Garella, P. & Guiso, L. (2000). Multiple versus single banking relationships: Theory and evidence. *The Journal of Finance* 55(3), 1133-1161.
- Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies* 51(3), 393-414.
- Doerr, S. & Schaz, P. (2021). Geographic diversification and bank lending during crises. *Journal of Financial Economics* 140, 768-788.
- Elsinger, H., Lehar, A., & Summer, M. (2006). Risk assessment for banking systems. *Management Science* 52, 1301–1314.
- Elyasiani, E., & Goldberg, L. G. (2004). Relationship lending: a survey of the literature. *Journal of Economics and Business*, 56(4), 315-330.
- Fescioglu-Unver, N. & Tanyeri, B. (2013). A comparison of artificial neural network and multinomial logit models in predicting mergers. *Journal of Applied Statistics*, 40, 712–720.
- Freixas, X., Parigi, B. M. & Rochet, J.C. (2000). Systemic risk, interbank relations, and liquidity provision by the Central bank. *Journal of Money, Credit and Banking* 32(3), 611-638.
- Gai, L., Lelasi, F., & Rossolini, M. (2016). SMEs, public credit guarantees and mutual guarantee institutions. *Journal of Small Business and Enterprise Development* 23(4), 1208–1228.
- Georg, C.P. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking & Finance* 37(7), 2216-2228.

Greenwood, R., Landier, A., & Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics* 115, 471-485.

Gurara, D., Presbitero, A., & Sarmiento, M. (2020). Borrowing costs and the role of multilateral development banks: Evidence from cross-border syndicated bank lending. *Journal of International Money and Finance* 100, February 2020, 102090.

Güngör, G. Y., & Sümer, T. P. (2018). The role of CGF guaranteed loans in terms of access to credit, cost and maturity. TCMB Blog, Central Bank of the Republic of Türkiye.

Hale, G. (2012). Bank relationships, business cycles, and financial crises. *Journal of International Economics* 88, 312-325.

Hale, G., Kapan, T., & Minoiu, C. (2020). Shock transmission through cross-border bank lending: Credit and real effects. *The Review of Financial Studies* 33, 4839-4882.

Hale, G. & Obstfeld, M. (2016). The Euro and the geography of international debt flows. *Journal of the European Economic Association* 14, 115-144.

Hekimoğlu, M.H., & Tanyeri, B. (2011). "Stock-market reactions to mergers of non-financial Turkish firms," *İktisat İşletme ve Finans* 26(308), 53-70.

Honohan, P. (2010). Partial credit guarantees: Principles and practice. *Journal of Financial Stability* 6(1), 1-9.

Hu, L., Han, J., & Zhang, Q. (2018). The impact of monetary and fiscal policy shocks on stock markets: Evidence from China. *Emerging Markets Finance and Trade* 54(8), 1856-1871.

Im, K.S., Pesaran, M.H. & Shin, Y. (1997). Testing for Unit Roots in Heterogeneous Panels'. Mimeo, Department of Applied Economics, University of Cambridge.

Jiménez Zambrano, G., Laeven, L., Martínez Miera, D., & Peydró, J. L. (2023). Public guarantees and private banks' incentives: evidence from the COVID-19 crisis. Documentos de Trabajo/Banco de España, 2318.

Kempf, E., Luo, M., Schäfer, L., & Tsoutsoura, M. (2023). Political ideology and international capital allocation. *Journal of Financial Economics* 148, 150-173.

Khwaja, A. I., & Mian, A. (2005). Do lenders favor politically connected firms? Rent provision in an emerging financial market. *The Quarterly Journal of Economics* 120(4), 1371-1411.

- Kredi Garanti Fonu. (n.d.-a). What is CGF? <https://www.CGF.com.tr/index.php/en/>
- Kredi Garanti Fonu. (n.d.-b). Our Shareholders. Credit Guarantee Fund. <https://www.CGF.com.tr/index.php/en/about-us/our-shareholders>
- Kredi Garanti Fonu. (n.d.-c). İşletmelere 200 Milyon TL'ye Kadar CGF Teminati. Credit Guarantee Fund. <https://www.CGF.com.tr/index.php/tr/duyuru-haber/CGF-den-haberler/82-isletmelere-200-milyon-tl-ye-kadar-CGF-teminati>
- Kredi Garanti Fonu. (2015). Annual Report. https://www.CGF.com.tr/images/faaliyet_raporu/2015_CGF_faaliyet_raporu_en.pdf
- Kredi Garanti Fonu. (2017). Annual Report. http://www.CGF.com.tr/images/faaliyet_raporu/CGF_ENG_FAALIYET_RAPORU.pdf
- Levin, A., Lin, C.F., & Chu, J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1), 1-24.
- Levine, R., Lin, C. & Xie, W. (2021). Geographic diversification and banks' funding costs. *Management Science* 67(5), 2657-2678.
- Li, S., Liu, Y. & Wu, C. (2020). Systemic risk in bank-firm multiplex networks. *Finance Research Letters* 33 (March), 101232.
- Liang, L. W., Huang, B. Y., Liao, C. F., & Gao, Y. T. (2017). The impact of SMEs' lending and credit guarantee on bank efficiency in South Korea. *Review of Development Finance* 7(2), 134-141.
- Lux, T. (2016). A model of the topology of the bank-firm credit network and its role as channel of contagion. *Journal of Economic Dynamics and Control* 66, 36-53.
- Mathieu, P., Pani, M., Chen, S., & Maino, R. (2019). Drivers of cross-border banking in Sub-Saharan Africa. IMF Working Paper. WP/19/146.
- Millon, M. H., & Thakor, A. V. (1985). Moral hazard and information sharing: A model of financial information gathering agencies. *The Journal of Finance* 40(5), 1403-1422.
- Minoiu, C. & Reyes, J. A. (2013). A network analysis of global banking: 1978–2010. *Journal of Financial Stability* 9, 168-184.
- Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control* 31, 2033-2060.
- NTV (2018, May 18). Günün öne çıkan 10 haberi (18 Mayıs 2018). Retrieved April

4, 2023, from https://www.ntv.com.tr/galeri/turkiye/gunun-one-cikan-10-haberi-18-mayis-2018,D7tRSjhwp0OxVqFV_qdoqA

OECD (2018), Financing SMEs and Entrepreneurs 2018: An OECD Scoreboard, OECD Publishing, Paris, https://doi.org/10.1787/fin_sme_ent-2018-en.

OECD (2019), Financing SMEs and Entrepreneurs 2019: An OECD Scoreboard, OECD Publishing, Paris, https://doi.org/10.1787/fin_sme_ent-2019-en.

Oh, I., Lee, J. D., Heshmati, A., & Choi, G. G. (2009). Evaluation of credit guarantee policy using propensity score matching. *Small Business Economics* 33(3), 335-351.

Ongena, S., & Smith, D. C. (2000). What determines the number of bank relationships? Cross-country evidence. *Journal of Financial Intermediation* 9(1), 26-56.

Ongena, S., & Şendeniz-Yüncü, İ. (2011). Which firms engage small, foreign, or state banks? And who goes Islamic? Evidence from Turkey. *Journal of Banking & Finance*, 35(12), 3213-3224.

Papaioannou, E. (2008). What Drives International Bank Flows? Politics, Institutions and other Determinants. *Journal of Development Economics* 88(2), 269-281.

Peek, J. & Rosengren, E.S. (2000). Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States. *American Economic Review* 90, 30-45.

Pichler, A., Poledna, S., & Thurner, S. (2021). Systemic risk-efficient asset allocations: Minimization of systemic risk as a network optimization problem. *Journal of Financial Stability* 52, 100809.

Poledna, S., Hinteregger, A. & Thurner, S. (2018). Identifying systemically important companies by using the credit network of an entire nation. *Entropy*, 20(10), 792.

Rajan, R.G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance* 47, 1367-1400.

Rajan, R., & Winton, A. (1995). Covenants and collateral as incentives to monitor. *The Journal of Finance* 50(4), 1113-1146.

Reinhardt, D. & Riddiough, S. J. (2015). The two faces of cross-border banking flows. *IMF Economic Review* 63, 751-791.

Roncoroni, A., Battiston, S., D'Errico, M., Hałaj, G., & Kok, C. (2021). Interconnected banks and systemically important exposures. *Journal of Economic Dynamics and Control* 133, 104266.

Shin, H. S. (2012). Global banking glut and loan risk premium. *IMF Economic Review* 60(2), 155-192.

Shim, I. & Shin, K. (2021). Financial stress in lender countries and capital outflows from emerging market economies. *Journal of International Money and Finance* 113, 102356.

Silva, T.C., da Silva Alexandre, M. & Tabak, B.M. (2018). Bank lending and systemic risk: A financial-real sector network approach with feedback. *Journal of Financial Stability* 38 (October), 98-118.

Sümer, T. P. (2019). Systemic risk and financial networks (Doctoral dissertation, Bilkent Üniversitesi, Türkiye.

Sümer, T. P. and Özyıldırım, S. (2019). Do banking groups shape the network structure? Evidence from Turkish interbank market. *International Review of Financial Analysis* 66, 101387.

Sümer, T.P. & Özyıldırım, S. (2021). Cross-border Transactions and Network Analysis: Evidence from Türkiye. CBRT Working Paper. Number: 21/22.

Şendeniz-Yüncü, İ. (2020). Finansal Sistemin Yapisi Ile Reel Ekonomi Arasindaki Dinamik Etkileşim. *Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 38(4), 869-890.

Tanyeri Günsür, B.& Bulut E. (2022). Investor reactions to major events in the sub-prime mortgage crisis. *Finance Research Letters* 47, 102703.

Topaloğlu-Bozkurt, A., & Tanyeri-Günsür, B. (2023). Pricing the net benefits of a public loan guarantee scheme in a developing market. *Economics Letters*, 232, 111353.

Tasca, P. & Battiston, S. (2016). Market procyclicality and systemic risk. *Quantitative Finance* 16, 1219-1235.

Tian, S., Yang, Y., & Zhang, G. (2013). Bank capital, interbank contagion, and bailout policy. *Journal of Banking & Finance* 37, 2765-2778.

TRT Haber (2016, December 2). Ekonomi Koordinasyon Kurulu toplandı. Retrieved April 17, 2023, from <https://www.trthaber.com/haber/ekonomi/ekonomi-koordinasyon-kurulu-toplandi-285914.html>

Upper, C. & Worms, A. (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion?. *European Economic Review* 48, 827-849.

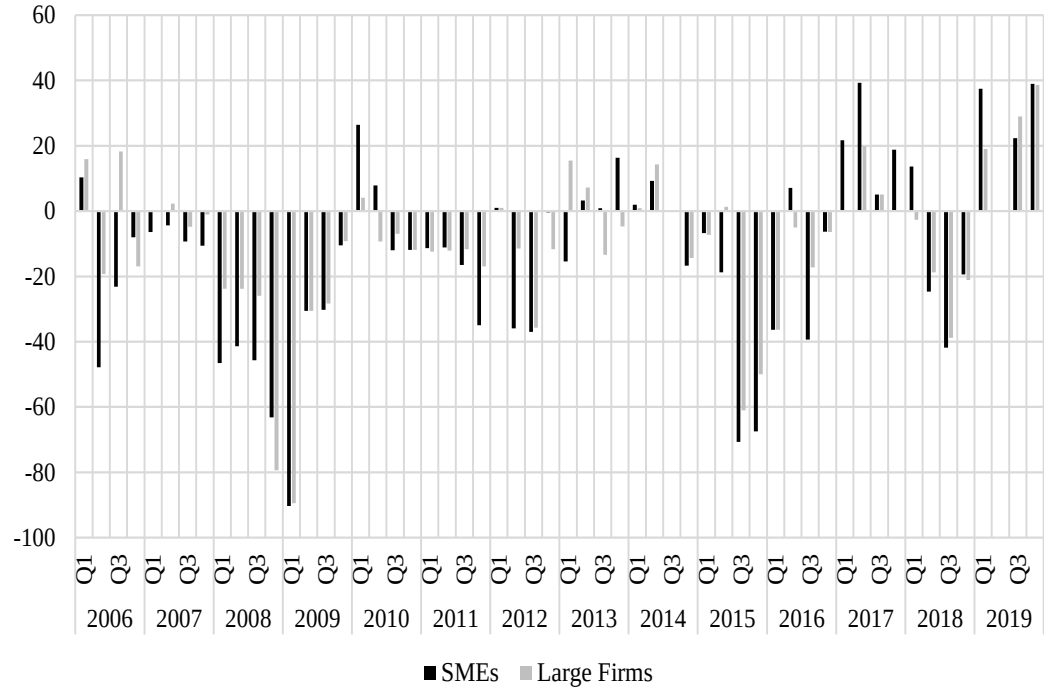
- Van Lelyveld, I. (2014). Finding the core: Network structure in interbank markets. *Journal of Banking & Finance*, 49 (December), 27-40.
- Vogel, R. C., & Adams, D. W. (1997). The benefits and costs of loan guarantee programs. *The Financier* 4(1), 22-29.
- Wilcox, J. A., & Yasuda, Y. (2019). Government guarantees of loans to small businesses: Effects on banks' risk-taking and non-guaranteed lending. *Journal of Financial Intermediation* 37, 45-57.
- Wouter, D. N., Andrej, M., & Vladimir, B. (2005). Exploratory social network analysis with Pajek. New York.
- Yağcı, M. (2019). Credit 15 guarantee scheme and small and medium-sized enterprise finance. *Unlocking SME Finance in Asia: Roles of Credit Rating and Credit Guarantee Schemes*, 337.
- Yıldırım, D. C., Unal, O. T., & Gedikli, A. (2015). Financial Problems of Small and Medium-Sized Enterprises in Türkiye. *International Journal of Academic Research in Business and Social Sciences* 5(1), 27.
- Yılmaz, I. and Tanyeri, B. (2016). Global Merger and Acquisition (M& A) activity: 1992–2011. *Finance Research Letters* 17, 110–117.
- Zhao, H., Li, Y., Sai, Q. & Ren, Y. (2023). Cross-border credit networks, banking risk contagion and suppression effects. *Social Networks* 73, 130-141.

APPENDIX

Supplement 1. TCMB Bank Loan Tendency Survey

Figure 3.A1 uses the Bank Loan Tendency Survey to tabulate the changes in lending standards. The index is the difference between the share of banks that eased lending standards (when compared to the previous quarter) from the banks that tightened. A negative (positive) value indicates that the percentage of banks tightening lending standards is larger (smaller) than the percentage of banks easing (TCMB, n.d.-a). Lending standards tightened during the global financial crisis and 2015 and 2016. The tightening in lending standards seems to have eased in 2017. Second, the number of firms approved for CGF-guaranteed loans increased from 4,376 in 2015 to 297,682 in 2017. The corresponding increase in loan volume was from 2.4 billion TL (0.8 billion USD) to 208 billion TL (55.2 billion USD). CGF funded 70.7 percent of the loan guarantees with Treasury support in 2015 and 99.5 in 2017 (CGF, 2015 and 2017). Banks eased lending standards, and the number of firms accessing bank loans exploded in 2017.

Figure 3.A1: Lending Standards for Loans to SMEs and Large Firms



The figure reports the aggregated quarterly responses of banks to the TCMB Bank Loan Tendency Survey question, "How have your bank's credit standards applied to the approval of loans or credit lines to enterprises changed over the past three months" for SMEs and large firms. A negative (positive) value indicates that the percentage of banks tightening lending standards is larger (smaller) than the percentage of banks easing (TCMB, n.d.-a, and b).