Portfolio Choice of Financial Institutions and Sovereigns: Implications for Financial Stability

Inauguraldissertation
zur Erlangung des akademischen Grades
eines Doktors der Wirtschaftswissenschaften
der Universität Mannheim

vorgelegt von
Diplom Volkswirt, Master of Science in Finance Frederik Eidam
Mannheim

Dekan: Prof. Dr. Dieter Truxius
Referent: Prof. Dr. Sascha Steffen
Korreferent: Prof. Dr. Jannis Bischof

Tag der mündlichen Prüfung: 25.04.2018

Hiermit wird nach Paragraph 12(4) der Promotionsordnung darauf hingewiesen, *dass die Veröffentlichung auf einer Dissertation der Universität Mannheim beruht.*

Meiner Familie

Acknowledgments

This dissertation was written while I was at the University of Mannheim. During this period, I benefited greatly from the encouragement and help of many people.

First of all, I would like to thank my supervisor Sascha Steffen for his invaluable advice, support, and trust in my abilities. He gave me the freedom to choose my research path, while providing constructive help. I am also thankful to him for introducing me to the scientific world of financial economics and the corresponding interactions that enriched my academic life.

Moreover, I would like to thank Steven Ongena for his support and the fruitful discussions during my research stay at the University of Zurich. I also highly benefitted from the stimulating research environment and the great hospitality of the Department of Banking and Finance at the University of Zurich. Anthony Saunder's insights on designing and framing our joint research projects were of great value to me, as were Jian Cai's very helpful insights on the implementation of empirical research. I also thank Jannis Bischof for being part of my dissertation committee.

While writing this thesis, I also benefitted from the stimulating research environment at the University of Mannheim, and in the ZEW research group for International Finance and Financial Management. In particular, I would like to thank Lea Steinrücke for her valuable feedback, encouragement, and for going through the ups and downs of this journey with me. I am furthermore grateful for Karolin Kirschenmann's advice, support, and encouragement. Moreover, I greatly benefitted from the advice on navigating through this long journey from Anne Kascha, Christoph Trebesch, and Oliver Sündermann. In addition, my thanks go to Tobias Etzel, Jasper Haller and Simona Helmsmüller.

I would like to express my deep sense of gratitude to my family, who has always been there and supported me over all the years. I am grateful for my parents, who taught me values that provide an indispensable inner compass to navigate my life. I am also very thankful for Naomi and Benaja, who can always make me smile and let me see the world through different eyes. My final thanks go to Claire for her love, support, and endurance. She always believed in me, and without her this journey would not have been possible.

Frederik Eidam

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Chapter 1

Introduction

Promoting the stability of the financial system is considered to be a key objective by politicians, policy makers and regulators to support worldwide economic development (e.g., ECB (2017), World Bank (2013)). Understanding that the portfolio choice of financial intermediaries and sovereigns plays an important role resulted in various pieces of regulation and guidelines with the aim to promote the stability of individual institutions and the financial system as a whole (e.g. BIS (2010), IMF and World Bank (2014)). However, the global financial crisis of 2007-2009 and the European sovereign debt crisis of 2010-2012 demonstrated that it still eludes us how this objective can be achieved. The global financial crisis demonstrated how quickly risks can spread across highly interconnected financial institutions causing a global systemic crisis and worldwide economic downturn. One important factor of these risk spillovers among financial institutions is commonality in asset holdings (e.g., Shleifer and Vishny (1992, 2011), Kiyotaki and Moore (1997)). In addition, the European sovereign debt crisis highlighted that the health of financial institutions and sovereigns are intertwined and that sovereign instability can be an important source of risk to the financial system (e.g., Laeven (forthcoming)). One important factor of sovereign instability is the maturity structure of sovereign debt, which affects sovereigns' exposure to rising funding costs and exclusions from financial markets.

This thesis studies the portfolio choice of financial institutions and sovereigns, and investigates its implications for financial stability. On the one hand, it investigates the portfolios' liability side of sovereigns by studying debt maturity as a key dimension of governments' debt portfolio structure. The focus is on strategic behavior in governments' maturity choice and on the Eurozone, which provides an ideal environment as strategic interactions among governments should be most pronounced in an integrated market. On the other hand, this thesis investigates commonality in banks' asset holdings as a key dimension of banks' asset choice. The focus is on banks' corporate syndicated loan portfolios in the U.S. market, which provides an ideal environment as corporate syndicated loan portfolios are a sizable part of banks' total assets.

Most of the literature on governments' debt maturity choice explores the role of funding costs and funding needs. Governments may trade-off long-term debt as a hedge against fluctuations in future funding costs, against higher repayment incentives associated with short-term debt to ensure future funding (Arellano and Ramanarayanan (2012)). Moreover, governments might prefer long-term debt to avoid rollover crises (Cole and Kehoe (2000)). However, short-term debt is usually cheaper than long-term debt, particularly during crises periods (Broner et al. (2013)). An alternative explanation is strategic behavior. One of the leading theories for strategic maturity choice from the corporate debt literature emphasizes "gap-filling" behavior of market participants (Greenwood et al. (2010)). According to this theory, governments would choose debt maturity to fill supply gaps across maturities, which result from varying aggregate financing patterns of governments.

The thesis adds to this literature by broadening our understanding of governments' debt maturity choice in general and investigating strategic behavior as a determinant of maturity choice in particular. Thereby, it establishes gap-filling as a new channel of governments' maturity choice, and highlights its implications for the resilience of government bond market liquidity. As empirical studies on governments' maturity choice have so far mainly focused on emerging economies and the U.S, this thesis also contributes by extending the literature to a setting where multiple governments issue debt in an integrated market, such as the Eurozone.

A different strand of the literature has theoretically shown that higher interconnectedness of financial institutions through common exposures in times of crisis can increase systemic risk through various forms of financial contagion (Allen et al. (2012a), Castiglionesi and Navarro (2010), Ibragimov et al. (2011), Wagner (2010)). Channels affecting financial contagion among financial institutions are, for example, direct linkages (Allen and Gale (2000), Allen and Babus (2009), Gorton and Metrick (2012), Giglio (2016)), information contagion (Chen (1999)), and commonality of asset holdings. As banks have similar exposure to assets such as syndicated loans, a decline in asset prices can affect the banking system, because of the direct exposure of banks to the same assets as well as fire sale externalities (e.g. Shleifer and Vishny (1992, 2011), Kiyotaki and Moore (1997)). Another relevant strand of the literature investigates loan syndication. While syndicate structures have been examined from different perspectives, only recently a few papers have emerged on how banks interconnect in the syndicated loan market by studying the evolution of syndicate structures (e.g. Sufi (2007), Cai (2010)). However, these studies are predominantly limited to the choice of participant lenders. Participants might be chosen in loan syndicates based on their prior relationships with both the borrower and the lead arranger (Sufi (2007)).

Linking to the literatures on financial institutions' interconnectedness through common exposures and the evolution of their interconnectedness through syndicated loan structures, this thesis aims at understanding the impact of banks interconnectedness through common exposures on systemic risk, and how banks become interconnected. It develops a novel measure of bank interconnectedness and offers new insights on the effects of banks' interconnectedness on bank-level systemic risk. In addition, it extends the literature on how banks become interconnected by investigating the role of similarity in lending expertise on banks' interconnectedness through corporate syndicated loan structures, and studies the effects of syndicated loan structures on loan pricing. Finally, this thesis also provides various policy implications.

This thesis is organized as follows. Chapter 2 investigates governments' debt maturity choice. Chapter 3 deals with the interconnectedness of banks through syndicated corporate loan portfolios, and Chapter 4 studies how banks become interconnected.

1.1 Government debt maturity choice – strategic behavior and liquidity implications[1]

Governments actively decide on the maturity structure of their debt portfolios by issuing debt across maturities. While governments' debt maturity affects creditor losses in debt restructuring, long-term interest rates, debt sustainability levels, exposures to fluctuating funding costs, and consequently governments' vulnerability to crises (e.g., Kim (2015), Beetsma et al. (2016), and Asonuma et al. (2017)), evidence on the determinants of debt maturity choice is scarce. Also, established theories predominantly focus on explaining government debt maturity choice through funding costs and funding needs (e.g., Cole and Kehoe (2000), Arellano and Ramanarayanan (2012), and Aguiar et al. (2016)). But with large variations in the maturity structure of governments' debt portfolios, it becomes clear that these explanations might not fit all circumstances. An alternative explanation is strategic behavior. One of the leading theories for strategic maturity choice from the corporate debt literature emphasizes "gap-filling" behavior of market participants (Greenwood et al. (2010)). According to this theory, governments would choose debt maturity to fill supply gaps across maturities, which result from varying aggregate financing patterns of governments. Since governments' gap-filling would imply that governments act as macro liquidity providers thereby adding significant risk absorption capacity to government bond markets, it would be an important channel strengthening the resilience of government bond market liquidity.

This study therefore provides an important contribution to the literature by investigating whether gap-filling is also an important determinant of maturity choice in the government bond market. Also, it is to my knowledge the first study to systematically analyze the determinants of governments' debt maturity choice across Europe. To this end, this chapter constructs a novel data set of Eurozone governments' debt maturity choice from 1999 to 2015. The data set not only covers maturity choices of individual debt issues, but also various aggregate bond auction results, as well as data on matched debt issuance announcements and debt auction results, which allows to disentangle demand and supply effects. The main result shows that governments increase long-term

[1]This chapter is based on the paper "Gap-filling debt maturity choice". The paper was presented at the University of Mannheim, Deutsche Bundesbank, University of Zurich, Goethe University Frankfurt, ZEW Mannheim, the German Debt Management Agency, the Muenster Banking Workshop 2016, and the German Finance Association Meeting 2017 in Ulm.

debt issues following periods of low aggregate Eurozone long-term debt issuance, and vice versa. Also, consistent with investors' preference for high quality and liquid government bonds (Krishnamurthy and Vissing-Jorgensen (2012)), higher rated governments engage more pronounced in gap-filling. Further, consistent with a higher degree of flexibility to adjust the maturity structure of their debt issues (Greenwood et al. (2010)), also less financially constrained governments undertake gap-filling more aggressively. At the same time, governments' gap-filling only occurred after the start of regulatory harmonization for insurers in the EU, which strengthened insurers' preferred habitat for long-term government Eurozone debt.

Analyzing the ECB's largest liquidity provision in history (namely, the ECB's three-year LTRO in 2011-2012) allows me to disentangle demand and supply effects. Following the ECB's three-year LTRO, peripheral governments largely unexpectedly and temporarily increased their short-term debt issuance (to accommodate peripheral banks demand for "carry trades"), while core governments engaged in gap-filling of longer maturity Eurozone government debt. It turns out that governments' strategic gap-filling behavior is a response to maturity-specific investor demand, rather than coordination of debt supply among governments. This result is also shown at the government debt auction-level, where Germany deviated from pre-announced issuance plans to fill the gap of longer maturity Eurozone government debt.

These temporary adjustments in the maturity structure of debt issuance following the ECB's three-year LTRO resulted in important financial implications for governments. The average residual maturity of total outstanding debt of peripheral and core governments' debt portfolios diverged, and did not converge thereafter. Correspondingly, these temporary debt issuance adjustments permanently increased peripheral governments' debt rollover requirements, thereby destabilizing their debt portfolios. In contrast, core governments' increase of longer maturity debt permanently stabilized their debt portfolios.

For policy makers, governments' strategic debt maturity choice behavior has important liquidity implications. Governments' gap-filling implies that governments act as macro-liquidity providers across maturities, thereby providing significant risk absorption capacity to government bond markets. Currently, there is a widespread concern about deteriorated resilience in government bond market liquidity since the financial crisis of 2007 to 2009. In contrast, governments' gap-filling behavior strengthens the resilience of government bond market liquidity. Consequently, changes to the financial architecture, such as the creation of safe government assets or the setup of a sovereign debt restructuring mechanism in the Eurozone, should be designed such that governments are able to continue providing this risk absorption capacity.

1.2 Banks' interconnectedness through syndicated corporate loan portfolios – impact on bank-level systemic risk[2]

The financial crisis of 2007-2009 demonstrated how large risk spillovers among financial institutions caused a global systemic crisis and worldwide economic downturn. Contagion among financial institutions results from different channels, such as direct linkages (Allen and Gale (2000), Allen and Babus (2009), Gorton and Metrick (2012), Giglio (2016)), information contagion (Chen (1999)), and commonality of asset holdings. As banks have similar exposure to assets such as syndicated loans, a decline in asset prices can affect the banking system, because of direct exposure of banks to the same assets as well as fire sale externalities (e.g. Shleifer and Vishny (1992, 2011), Kiyotaki and Moore (1997)). Recent theoretical work has shown that higher interconnectedness through common exposures at times of crisis can increase systemic risk through various forms of financial contagion (Allen et al. (2012a), Castiglionesi and Navarro (2010), Ibragimov et al. (2011), Wagner (2010)). Consequently, policy makers around the world initiated new efforts to improve their measurement and monitoring of interconnectedness among banks, such as interconnectedness resulting from common exposures to syndicated corporate loans. This study amends the literature by developing a novel measure of interconnectedness among banks and studying interconnectedness in the form of common exposures among financial institutions examining banks' exposure to large syndicated loans.

To measure commonality in banks' syndicated loan portfolio, we develop a novel measure of interconnectedness for which the key component is the similarity between two banks' syndicated loan portfolios. The similarity is measured as the Euclidean distance between two banks based on their exposures to specific borrower industries or regions. We then aggregate the distance of one bank with all other banks to our bank-level interconnectedness measure, using different weights such as equal weights, size, and relationship. We find that interconnectedness is driven mainly by bank diversification, less by bank size or overall loan market size. The time-series evolution of our interconnectedness measure is consistent with the interpretation of elevated systemic risk through contagion arising from common exposures. Also, we aggregate our bank-level interconnectedness measure to a market interconnectedness index. We find evidence that banks have greater overlap with larger banks consistent with the literature on bank moral hazard and herding behavior

[2]This chapter is based on the paper "Syndication, interconnectedness, and systemic risk", which is joint work with Jian Cai from Washington University in St. Louis, Anthony Saunders at the Stern School of Business at New York University, and Sascha Steffen from the Frankfurt School of Finance and Management. The paper was presented at the 2012 AEA Annual Meeting, the 2012 EFA Annual Meeting, the CESifo "The Banking Sector and The State" Conference, the 6th Swiss Winter Finance Conference on Financial Intermediation, the 2014 Banque de France – ACPR – SoFiE conference on Systemic Risk and Financial Regulation, the 2014 Concluding Conference of the Macro-prudential Research (MaRs) Network of the European System of Central Banks, the Third BIS Research Network Meeting on Global Financial Interconnectedness, and the 2016 AFA/AEA Annual Meeting, and at University of Muenster and Goethe University Frankfurt. It has been published at the Journal of Financial Stability.

(e.g. Acharya and Yorulmazer (2008)) and banks exploiting government guarantees (e.g. Eisert and Eufinger (2017)).

In the final part of the paper, we relate our bank-level interconnectedness indexes to different measures of systemic risk, such as SRISK, DIP, and CoVaR. Similar to approaches used in stress tests that have been conducted in the U.S. and Europe since 2008, the construction of these measures is to estimate losses in a systemic stress scenario and determine a bank's equity shortfall after accounting for these losses. These measures capture asset price as well as funding liquidity risks associated with interconnectedness using market data (Acharya et al. (2014)).

The main finding is a robust and significantly positive relation between our interconnectedness measure and various systemic risk measures, but only during recession periods. Consistent with the theoretical papers cited above, interconnectedness thus amplifies systemic risk during recessions when asset commonality can cause various forms of contagion such as fire-sales. Another way of interpreting this result is that interconnectedness of banks – that builds up during normal times – is a useful tool to forecast cross-sectional differences in banks' contribution to systemic risk, if a severe crisis occurs. Overall, our results highlight that institution-level risk reduction through diversification ignores the negative externalities of an interconnected financial system.

For banks and regulators, our results have several important implications. First, market based measures of systemic risk are informative during bad times, because they pick up fundamental risks of banks precisely in a moment when banks are worried about their counterparties' exposures. Second, we provide an important link from balance sheet risk to market-based risk measures, i.e. common exposures to large syndicated loans. Regulators with more detailed data can extend our analyses investigating and monitoring specific industry overlap, common exposures to leveraged loans or, for example, exchange rate risks that might be hidden in these loans. Third, an institution-oriented approach to assessing and limiting systemic risk exposure is insufficient as the narrative of the recent financial crises suggests. Fourth, the Financial Stability Oversight Council (FSOC), which was created in the U.S. following the Dodd-Frank Wall Street Reform after the 2008-2009 financial crisis, has the mandate to monitor and address the overall risks to financial stability. We propose using interconnectedness through large corporate loans as part of FSOC's systemic risk oversight and monitoring system.

1.3 How do banks become interconnected? Evolution of syndicated loan structures and effects on loan pricing[3]

Over the last two decades, banks have become increasingly interconnected and the recent global financial crisis highlighted the vulnerabilities of a highly interconnected financial system. One source of interconnectedness among banks has been corporations growing funding needs, both in size and complexity. The banking industry, however, is competitive by nature. As a result, banks face a fundamental question: Whom should they collaborate with while competing with the rest? If banks differentiate competitors by how close they are in terms of their lending expertise, the question translates into the following: Should banks collaborate with distant or close competitors? This chapter seeks to investigate this question by relating banks' lending expertise to the organizational form of loan syndicates and analyzes the effects on loan pricing.

While syndicate structures have been examined from different perspectives, such as information asymmetry (e.g., Lee and Mullineaux (2004)), this line of research has usually taken the organizational form of syndicates as given. Only recently the evolution of the organizational form of loan syndicates has been studied (e.g., Sufi (2007)), but predominantly investigates syndicate member choice. This study is the first to examine syndicate structures from the perspective of similarity in lending expertise among syndicate lenders, and studies syndicate formation more broadly than previous studies. In particular, we investigate motives for banks to interconnect themselves with close competitors – that is, forming close syndicates with high similarity in banks' lending expertise. On the one hand, lenders with higher similarity in lending expertise might have lower production costs to produce borrower-specific information (Boot (2000)). On the other hand, informational monopolies of close syndicates might enable lenders to "hold-up" the borrower (Sharpe (1990), Rajan (1992)). In addition, this "hold-up" might be particularly pronounced during periods of low market concentration, where the scope for price collusion in markets with syndicates increases (Hatfield et al. (2017)).

This study measures the similarity in lending expertise among banks in a syndicate, by extending our distance measure between two banks from Chapter 3 to the syndicated loan level. Our object of study is the U.S. syndicated loan market. Analyzing syndicate formation, the results show that besides for very distant loans, closer syndicates are associated with smaller and more concentrated syndicates. Also, lead arrangers are more likely to choose very close lenders into more senior roles (co-leads and co-agents) of the syndicate, and also participant lenders choice becomes more likely with smaller distance. Further, lead arrangers allocate higher loan shares to lenders with smaller distance across all loan

[3] This chapter is based on the paper "Loan syndication structures and price collusion", which is joint work with Jian Cai from Washington University in St. Louis, Anthony Saunders at the Stern School of Business at New York University, and Sascha Steffen from the Frankfurt School of Finance and Management. The paper was presented at the University of Mannheim, Federal Reserve Bank of Cleveland, University of Missouri-St. Louis, University of Muenster, Goethe University Frankfurt, Washington University in St. Louis, ZEW Mannheim, the Frankfurt School of Finance and Management, and 2017 Arne Ryde Conference on Financial Intermediation.

roles. Analyzing retained loan share of lead arrangers across loans with different degrees of information asymmetries shows that lead arrangers do not retain higher loan shares in close syndicates with higher information asymmetries. This finding is consistent with the conjecture of improved screening and monitoring of close syndicates, and might indicate that lead arrangers do not have to signal credit quality, or mitigate moral hazard by retaining larger loan shares when syndicate lenders possess similar very lending expertise. These results thus suggests that similarity in banks' lending expertise is an important determinant in the evolution of syndicated loan structures.

In addition to these effects on loan syndication structures, similarity in lending expertise among banks might also affect loan pricing as discussed above. Analyzing the net effect of improved screening and price collusion reveals that closer lender distance resulted in cheaper loan pricing until 2009, while it increased loan pricing since 2010. Disentangling these two opposite effects suggests that lenders in close syndicates passed on lower production costs from improved screening and monitoring to the borrower across the entire sample period. At the same time, close syndicates only engaged in price collusion since 2010. Consistent with our conjecture above, we finally show that low market concentration fosters price collusion, and close syndicates only engage in price collusion during periods of low market concentration.

For policy makers, these results highlight an important mechanism of how banks become interconnected in the financial system. Also, banks interconnectedness through syndicated corporate loans matters, as it increases banks systemic risks during recessions as shown in Chapter 3. Understanding the underlying economic mechanisms leading to higher interconnectedness among banks is important to design financial regulation that trade-off the benefits and risks of an interconnected financial system.

Chapter 2

Government debt maturity choice – strategic behavior and liquidity implications

2.1 Introduction

Governments actively decide on their debt maturity structure by issuing debt across maturities. The maturity structure of government debt portfolios is important as it affects creditor losses in debt restructurings, long-term interest rates, exposure to fluctuating funding costs, debt sustainability levels, and consequently governments' vulnerability to crises (e.g., Kim (2015), Beetsma et al. (2016), and Asonuma et al. (2017)). There are a number of established theories of government debt maturity choice, but these theories predominantly focus on funding costs and funding needs (e.g., Cole and Kehoe (2000), Arellano and Ramanarayanan (2012), and Aguiar et al. (2016)). An alternative explanation is strategic behavior. One of the leading theories for strategic maturity choice from the corporate debt literature emphasizes "gap-filling" behavior of market participants (Greenwood et al. (2010), hereafter GHS (2010)). According to this theory, governments would choose debt maturity to fill supply gaps across maturities, which result from varying aggregate financing patterns of governments.[1] However, gap-filling has so far only been studied for corporates (GHS (2010), Badoer and James (2016), and Foley-Fisher et al. (2016)). Governments' gap-filling would nevertheless be of particular importance, because governments acting as macro liquidity providers would add significant risk absorption capacity to government bond markets.

In this paper, I investigate whether gap-filling is also an important determinant of maturity choice in the government bond market. I use the Eurozone as a unique laboratory,

[1] According to the gap-filling theory, governments have a preference for a specific diversification of their debt maturity. However, aggregated supply changes combined with investors' preference for long-term debt and arbitrageurs' limited availability of capital can lead to a relative price change between short- and long-term debt. To reduce expected funding costs, governments are willing to adjust their supply of long-term debt.

as multiple governments share the same institutional setup, but separately choose debt maturity. After analyzing gap-filling over the full sample period, I address possible endogeneity concerns in an event study by exploiting changes in peripheral governments' maturity choice (induced by peripheral banks' "carry trades") following the ECB's three-year LTRO in 2011-2012.[2] In this setup, I examine three related questions: First, do governments engage in gap-filling maturity choice? Second, how does governments' gap-filling vary over time? And third, for which types of governments is gap-filling more pronounced?

I hypothesize that gap-filling maturity choice also occurs in the government bond market, because investors prefer the high quality and liquidity of government bonds (Krishnamurthy and Vissing-Jorgensen (2012), hereafter KVJ (2012)). Rather than substituting government debt with corporate debt within a country (as in GHS (2010)), investors seem to prefer substituting government debt across countries. In the Eurozone, investors can easily substitute government debt across multiple countries for the following four reasons: (1) a common currency is shared across governments, (2) monetary policy is centralized across governments, (3) credit quality is similar across multiple governments, and (4) financial regulation is largely identical across governments. In addition, financial regulation and central bank open market operations grant government debt preferential treatment–thereby further incentivizing investors to purchase government debt. Most importantly, financial regulation grants reduced (up to zero) capital charges and no large exposure limits to government debt. And the ECB classifies government debt as first category collateral in its open market operations, independent of their actual liquidity. Finally, substitution with corporate debt is much more restricted in Europe compared to the U.S., because European corporations fund themselves mainly through bank debt rather than bond debt.

Importantly, gap-filling should be most pronounced for governments' long-term (greater than 10 years) bond issues, because of higher duration risk capital for arbitrageurs (Badoer and James (2016)). As price volatility rises with a bonds maturity due to higher discounting of future cash flows, regulatory capital requirements usually increase with maturity. Moreover, a large class of investors with long-term liabilities, such as life insurance companies and pension funds, prefers purchasing long-term government debt as maturity matching is most effective to reduce capital requirements and comply with financial regulation.

In the cross-section, gap-filling should be more pronounced for less financially constrained and higher rated governments. Less financially constrained governments might engage more aggressively in gap-filling, due to their higher flexibility to adjust the maturity structure of their debt issues (GHS (2010)). Higher rated governments might undertake gap-filling more aggressively, as investors prefer the high quality of government bond securities (KVJ (2012)).

[2]"Carry trades" constitute of purchasing high-yielding (peripheral) government bonds funded by cheap ECB funding, and depositing these (peripheral) government bonds as collateral at the ECB (see, for example, Acharya and Steffen (2015)).

To empirically analyze governments' gap-filling, I construct a new panel data set of 9,098 individual debt issues of 15 Eurozone governments between 1999 and 2015 from Bloomberg. To my knowledge, I am the first to compile such a large data set of European government debt issues. For the event study, I also collect data on individual bond auctions and hand-collect data on debt issuance announcements for a smaller set of governments around the ECB's three-year LTRO in 2011-2012. This granular issuance- and auction-level data allows me to precisely observe governments' debt maturity choice. Importantly, it also allows me to split debt issues in multiple maturity buckets as in Badoer and James (2016) and analyze gap-filling purely on a flow basis–that is using fluctuations in the flow of aggregate Eurozone government long-term debt issues to explain the flow of an individual government's debt issues across maturities.[3] In comparison, previous gap-filling studies use the stock of long-term U.S. government debt to explain the flow or the stock of long-term U.S. corporate debt. As a result of strict budget rules for governments in the Eurozone, total debt issuance amounts within a period are fixed by governments' maturing debt and budget deficits. Compared to corporates that can also adjust total debt issuance amounts, Eurozone governments are restricted to adjusting the debt issues' maturity composition only.

My government bond data shows that deal characteristics of government debt issues are very similar across countries. In addition, governments frequently issue debt across maturities, enabling governments to easily shift debt issuance amounts across the maturity spectrum. Overall, total issuance amounts are predominantly short-term (up to one year, on average 50.5%), and long-term (greater than ten years, on average 18.7%). Finally, and important for analyzing gap-filling, there is substantial variation in aggregate Eurozone government long-term debt issuance over time.

In a first step, I examine whether governments engage in gap-filling. Consistent with gap-filling, I find that governments significantly increase long-term debt issues (and significantly reduce short-term debt issues) following periods of low aggregate Eurozone long-term government debt issuance, and vice versa. Governments perform gap-filling by shifting almost euro-for-euro between short-term and long-term debt issues, leaving medium-term maturity buckets largely unaffected. Controlling for government-level seasonality in debt issuance across all maturity buckets shows that gap-filling is a temporary deviation from established debt issuance pattern.

In a second step, I investigate the variation of governments' gap-filling over time. According to the gap-filling theory, gap-filling only occurs under partially segmented markets and limits to arbitrage. Partial segmentation might have increased as a result of harmonizing EU insurance regulation (Solvency II), as it strengthened insurer's incentives for maturity matching. Limits to arbitrage might have become more relevant since the last two financial crises and subsequent increases in financial regulation. Consistent with the gap-filling theory, I only find governments' gap-filling behavior after the start of harmonizing EU insurance regulation in late 2009.

[3] My results are also robust to controlling for the stock of outstanding long-term debt.

In a third step, I examine the cross-section of governments' gap-filling. As discussed above, gap-filling might be more pronounced for less financially constrained and higher rated governments. I find evidence consistent with these two cross-sectional predictions. In particular, when I sequentially group governments across different dimensions of financial constraints, I find significantly larger gap-filling for governments with lower indebtedness, smaller size, lower financing needs, lower budget deficits, and higher future economic growth.

The main concern with my gap-filling results is that governments might have coordinated their debt supply, instead of responding to investor's maturity-specific demand. To address this endogeneity concern, I exploit peripheral governments increase in shorter maturity debt issuance to accommodate banks demand for "carry trades" following the ECB's three-year LTRO in 2011-2012. These adjustments effectively resulted in a largely unexpected temporary negative credit supply shock of longer maturity Eurozone government debt. Consistent with gap-filling, I find that core governments responded by temporarily increasing longer maturity debt issues by 16.5%-points to fill the supply gap. Measures of excess demand in governments' longer maturity bond auctions, and changes in the slope of governments' yield curve are consistent with core governments responding to investor demand. In robustness checks, I also provide evidence that the gap-filling result is (1) not driven by confounding events during the Eurozone crisis; (2) not driven by restricted maturity choices of peripheral governments; (3) not driven by investor demand for safe assets; and (4) constitutes a deviation from governments' pre-announced issuance patterns.

These temporary adjustments in the maturity structure of debt issuances following the ECB's three-year LTRO resulted in significant financial implications. In aggregate, the average residual maturity of total outstanding debt of peripheral and core governments diverged by 0.6 years in the LTRO-period, and did not converge thereafter. Further, peripheral governments' debt rollover requirements until 2016 increased by 51.4bn EUR (or 3.3% of GDP) for Italy and 49.1bn EUR (or 4.7% of GDP) for Spain. In contrast, funding cost reduced by just 0.07% of GDP for Italy (with a budget deficit of 2.9% of GDP) and 0.05% of GDP for Spain (with a budget deficit of 10.4% of GDP) compared to not adjusting their debt maturity structure in response to the ECB's three-year LTRO. Consequently, peripheral governments exploited banks "carry trade" demand as a temporary relief on debt rollover, despite its negative implications for future debt rollover amounts. In contrast, core governments' gap-filling of long-term debt permanently reduced debt rollover requirements by 74.2bn EUR (or 1.1% core governments GDP). In sum, these maturity adjustments permanently stabilized core governments' debt portfolios, while it permanently destabilized peripheral governments' debt portfolios.

My analysis contributes to three strands of the literature. First, my paper contributes to the literature on segmented bond markets across maturities (e.g. Vayanos and Vila (2009), Greenwood and Vayanos (2014)) and the interaction of debt maturity choices between corporates and the government (for example, GHS (2010), Badoer and James (2016), and Foley-Fisher et al. (2016)). This literature shows that segmented bond markets across maturities can arise from investors' preferred habitat for specific maturities, which induces corporates to strategically fill maturity-specific supply gaps of government debt. In contrast, my paper is the first to investigate gap-filling also in the government bond market. In addition, I study gap-filling outside the U.S., and also analyze the cross-section of governments' gap-filling.

Second, my paper adds to the literature studying the determinants of governments' debt maturity choice (for example, Arellano and Ramanarayanan (2012), Broner et al. (2013), and Bai et al. (2015)).[4] In summary, these empirical papers typically concentrate on the effect individual country-specific credit market conditions, such as the spread, and investigate debt maturity choice in emerging economies. In contrast, I focus on interactions in governments' maturity choice across multiple governments. In addition, my study is the first to systematically analyze the determinants of governments' debt maturity choice across Europe and carefully controls for a variety of country-level credit market and macroeconomic conditions.

Third, my paper also contributes to the recent literature on the effects of unconventional monetary policies on government bond markets (for example, Joyce and Tong (2012), Eser and Schwaab (2016), and Krishnamurthy et al. (2017)). These papers predominantly investigate the effect on bond prices and CDS spreads, ignoring the effect on bond quantities. My paper is the first to investigate the effects of an unconventional monetary policy on bond quantities. In addition, my paper shows that adjustments on bond quantities of directly affected governments can induce strategic interactions of other governments.

The paper proceeds as follows. Section 2 introduces the institutional setting. Section 3 describes the data and presents summary statistics. Section 4 empirically investigates gap-filling in the government bond market. Section 5 addresses endogeneity concerns in an event study using the ECB's three-year LTRO. Section 6 concludes and draws some policy implications.

2.2 Institutional setting

2.2.1 Government debt management

The task of governments' borrowing and debt management is performed by government debt management offices (DMOs). Despite a strong interdependence of debt management with the remaining fiscal policy and monetary policy, DMOs in the Eurozone are separated from other parts of fiscal policy and operate independently from monetary policy. Guided by a micro portfolio approach of debt management, DMOs main objective constitutes a classical Markov problem: to reduce government's financing costs over a medium to long

[4]Other papers explore the optimal maturity structure of entire debt portfolios and their implications on optimal taxation and insurance against fiscal shocks, among others, Barro (1979), Lucas and Stokey (1983), Angeletos (2002), Buera and Nicolini (2004), and Debortoli et al. (2017).

horizon, while limiting fiscal risks (that are fluctuating funding costs, and rollover risks).[5] A key element to achieve this objective is debt maturity.

This objective, however, inherits a trade-off on debt maturity. Due to the monetary premium for short-term government debt, funding costs for shorter maturities are usually cheaper than for longer maturities. Yet, as shorter maturity debt has to be refinanced more frequently than longer maturity debt, higher total annual issuance amounts increase governments' exposure to fluctuating funding costs and rollover risk. As a result of this trade-off, governments usually diversify their debt maturity structure and issue debt with both shorter and longer maturities.[6]

In addition, DMOs additionally aim to achieve resilient secondary market liquidity for main benchmark maturities (for example, one, three, five, or ten year bonds). To ensure deep secondary markets, regular debt issues in each benchmark maturity are required, which might potentially conflict with the maturity trade-off of its main objective. Specifically, once credit market conditions change, governments might be slow to adjust the maturity of debt issues to ensure deep secondary market liquidity.

The DMOs' debt maturity decisions are operationalized in their funding strategy. Therein, government's total borrowing requirements (comprised of debt redemptions and primary surplus/deficit) are exogenous to the DMO, as they are a result of past debt issuance decisions and current financing needs decided by the remaining fiscal policy. Consequently, the DMO decides on the allocation of this fixed amount across the maturity spectrum. To ensure predictability of debt issues and sufficient demand by investors at each auction, DMOs in the Eurozone announce information of their funding strategy in advance. A general overview is provided at the annual level, where the DMO announces its predicted annual funding requirements, maturity(-range) specific auction dates, and partially the intended aggregated annual issuance amount of money market (up to one year maturity) and capital market (above one year maturity) debt issues. In contrast to emerging market debt issuances where auction dates are dependent on credit market conditions, for Eurozone governments the date of government bond auctions is therefore exogenous to credit market conditions around the auction date. Despite pre-determined auction dates (and for some DMOs also indications on the respective maturity), regular debt issues across the maturity spectrum and variations in issue amounts allow DMOs to maintain a high degree of freedom on their overall maturity choice at this stage. Usually at a quarterly level, DMOs determine auction- or issuance-level specific targets on debt issuance amounts, which to a large degree determine governments' debt maturity choice. While, DMOs officially keep the option to adjust their funding strategy depending on market conditions and funding

[5]See the "Revised Guidelines for Public Debt Management" by the IMF and the World Bank from 2014: https://www.imf.org/external/np/pp/eng/2014/040114.pdf

[6]DMOs can also alter this trade-off by entering into interest rate swaps. However, issuing long-term debt and entering into interest rate swaps to pay lower short-term yields increases the volatility of debt servicing costs. In the Eurozone, DMOs' outstanding interest rate swaps are at most small, and over time DMOs partially even inter into offsetting interest rate swap positions. Also, there is anecdotal evidence that increases in interest rate expenditures resulting from interest rate swaps are more difficult to communicate to the Ministry of Finance.

requirements. Historically however, debt issues have rarely been canceled and realized debt issues are often similar as planned. Consequently, DMOs in the Eurozone determine their debt maturity choice largely at a quarterly level.

2.2.2 Investor demand for government debt

As government bonds are a large part of bond market in general, various investors demand government debt. In the primary market, each government restricts the number of banks (so-called primary dealers) that are allowed to bid in government bond auctions. These banks, however, usually receive orders from other investors so that also other investors have indirect access to debt issues in the primary market. Additionally, all investors can buy and sell government bonds in secondary markets.

Since the aftermath of the global financial crisis in 2007-2009, new regulatory reforms further stipulated banks, and insurance companies to purchase government bonds. For banks, new liquidity regulation under Basel III (the liquidity coverage ratio, and net stable funding ratio) requires banks to hold government bonds as liquidity reserves. Further, as high quality government bonds possess minimal credit risk and high liquidity, banks usually use it as collateral for short-term borrowing. And despite evidence on its credit risk from the European sovereign debt crisis, government bonds continue to hold zero-risk weight in banks regulatory capital calculations and government debt is exempt from concentration limits. For European insurers, the new Solvency II regulation also exempts government bonds from credit and concentration risk under the standard formula in the solvency capital requirements (SCR) calculation.[7] In addition, Solvency II particularly incentivizes insurers to purchase government debt with specific maturities. Specifically, assets that perfectly match the maturity of liabilities are exempt from interest rate risks in the computation of insurers' capital requirements. Given that longer maturity liabilities pose particularly high interest rate risk due to their high discounting effect, insurers are particularly incentivized to purchase long-term government debt. This is particularly the case for life insurance companies, where interest rate risk resulting from maturity mismatches of assets and liabilities are often the largest component of capital requirements.

The transition to the low yield environment further reinforced these incentives. Lower yields increase asset values as future bond payments are discounted less, so that capital charges for asset holdings - that are usually proportional to assets values - correspondingly increase. As lower yields also increase the present value of long-term liabilities and widen existing duration mismatches between assets and liabilities, falling long-term interest rates even induce insurance companies to increase purchases of long-term government bonds at rising prices (Domanski et al. (2017)).

These regulatory reforms incentivize large classes of investors to buy governments bonds, so that aggregated demand for government debt might have become more inelastic. Moreover, inelastic demand might have been particularly developed for longer maturity gov-

[7]Nevertheless, SCR computed by internal models have to account for sovereign risk.

ernment bonds, given insurers changed incentives to match the maturity of long-term liabilities to reduce regulatory capital requirements. An increase in the average duration of outstanding government debt in Europe from six to seven years between 2008 and 2016 provides indicative evidence for increased demand for long-term European government debt.[8]

2.3 Data and descriptive statistics

2.3.1 Data

To analyze interactions in governments' maturity choice, I collect data on government's individual bond issuances between January 1999 and September 2015 for 15 Eurozone governments: Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.[9] The starting year of the sample differs across governments, and depends on the date when governments joined the Eurozone.[10] Data on individual government bond issuances into the primary market are collected from Bloomberg, and contains information on the usual characteristics of government bond issuances. I exclude from my analysis bond issuances that are tied to specific infrastructure projects, that are issued by fully owned public corporations owned by the central government (for example, energy companies, nationalized banks, transportation companies) and government investment funds, and that are obtained as part of ESM financial assistance programs.[11] I exclude these bond issuances, because the maturity choice is likely to be aligned with the time horizon of specific investment or financing decisions, and/or the maturity choice was likely determined to a large degree outside the scope of the central government.

I restrict my sample to central government debt issuances, because strategic maturity choices most likely occur at the highest level of government for two reasons. First, as central government debt in the Eurozone is usually the majority of total government debt, DMOs at the central level consequently issue most of the total governments' debt. Second, strategic maturity choices might be more pronounced at the central level compared to multiple local governments. For example, at the local level debt issues might be more inclined to match maturities of investment projects, and maturity choice might be less sophisticated than at the center. In addition, focusing on central government debt in a multi-country setting ensures cross-country comparability (see De Broeck and Guscina (2011)). Despite limiting my analysis to central government debt, the maturity structure

[8]See "The bond market is transformed: fewer vigilantes; more forced buyers" in the Economist on Oct 22nd, 2016.

[9]These are all current Eurozone governments besides Estonia, Latvia, Lithuania, and Luxembourg, which all have zero or very low levels of central government debt and consequently only sporadically issue central government bonds. Also, Latvia (2014) and Lithuania (2015) only joined the Eurozone at the end of the sample period.

[10]The following governments joined the Eurozone after their inception in 1999: Greece (2001), Cyprus (2008), Malta (2008), Slovenia (2007), and Slovakia (2009).

[11]Correspondingly, I exclude periods, in which governments did not have access to financial markets.

remains however very similar than those reported for total government debt in the ECB's Statistical Data Warehouse (SDW).

My focus on Eurozone governments stems from their unique institutional setup that allows me to investigate gap-filling in the government bond market. The Eurozone currently consists of 19 governments, which predominantly issue debt denominated in euro and are close substitutes in the Eurozone government bond market. Many countries are of high credit quality, and government bond markets are very liquid; two major bond characteristics preferred by investors (KVJ (2012)). In addition and as discussed above, financial regulation provides investors with different incentives to purchase government debt rather than substituting with (high quality) corporate debt. Also, the ECB classifies government debt as first category collateral in its open market operations, and only accepts euro-denominated government debt as collateral. Correspondingly, the start of my sample period is motivated by the start of the Eurozone, which abolished national currencies of Eurozone governments and thus increased the substitutability of Eurozone government debt.

To address endogeneity concerns in the event study, I also collect data on individual debt auction results and government's debt issuance announcements for a smaller set of governments around the ECB's three-year LTRO in 2011-2012. Specifically, I collect data on individual debt auction results for France, Germany, Italy, and Spain and hand-collect data on debt issuance announcements for Germany and Italy between 2010 and 2014. Also, I expand the bond issuance database by central government bonds issued prior to 1999 and maturing in 2012 or thereafter for computing outstanding debt maturity profiles.

My government bond data base is complemented by government-level data on macroeconomic conditions from Datastream and Bloomberg at quarterly, or yearly frequency. These variables are the government's debt/GDP ratio, the total change in the debt/GDP ratio in the previous four quarters, total real GDP growth during the previous four quarters, the countries consumer price inflation (CPI) during the prior year, a recession dummy computed based on two subsequent quarters of negative GDP growth, and a non-investment grade rating dummy based on S&P's long-term local currency government rating. In addition, I complement the dataset with data on credit market conditions from Bloomberg at the quarterly, or daily frequency. These credit market condition measures are the term structure measured as the yield differential between 10-year and 6-month government debt, the yield level as measured by the governments' 6-month yield, and the yield spread of 10-year government debt securities to 10-year German bunds. For the cross-sectional analysis, I also collect data on a countries size as measured by its GDP, and governments' budget deficit at quarterly, respectively yearly frequency. To examine gap-filling behavior, my measure for the supply of aggregated Eurozone long-term government debt is the log of the aggregated deal amounts (converted to euro) of Eurozone government debt issuances with maturities above ten years (hereafter AMT10).

The benefits of the AMT10 measure is that it precisely captures the new supply of long-term Eurozone government debt to investors. As discussed above, long-term government debt is more likely to be held to maturity by investors, so that new supply of long-term Eurozone government debt substantially influences the availability of long-term Eurozone government debt in the market. Investors - such as life insurance companies that aim to invest new premiums from customers in government bonds to match long-term liabilities - create demand for new long-term Eurozone government debt. Further, the supply of new government long-term debt issues varies substantially over time (see Figure 2.1), which is contained in the AMT10 measure. A potential drawback of the AMT10 measure is that it does not reflect the total supply of outstanding Eurozone long-term government debt. Nevertheless, total supply of Eurozone long-term government debt is relatively stable over time and variations predominantly arise due to new Eurozone government long-term debt issuances. To address this concern in the empirical analysis below, I include country-year fixed effects in robustness specifications to control for the changing level of government-level outstanding long-term debt over time (the results continue to hold).

2.3.2 Descriptive statistics

The main data set contains 9,098 government debt issuances from Bloomberg between January 1999 and September 2015. Table I shows summary statistics of deal characteristics, issuer characteristics, market characteristics, and the number of individual governments across five maturity buckets. The maturity buckets reflect major issuance maturities of government securities and are similar than those used by Broner et al. (2013). Panel A of Table 2.1 highlights that long-term (above 10 years) debt issues comprise only 677 debt issues (or 7.44% of total debt issues), however the mean issuance amount is four times larger than short-term (up to one year) debt issues. In addition, consistent with the monetary premium for short-term government debt, Eurozone governments predominantly issue short-term (6,406 debt issues, or 70.41% of total debt issues). Also as described above, deal characteristics are generally very similar across Eurozone governments. For example, 87% of total long-term debt issues are denominated in euro and about 95% of total long-term issues are not puttable or callable (and thus repay at final maturity).

Panel B of Table 2.1 shows issuer characteristics. Consistent with Eurozone governments being unable to dilute nominal debt with higher inflation as monetary policy in the Eurozone is not set at individual governments national level (but centrally at the ECB), mean inflation is about 1.8% for both short-term and long-term debt issues. Consistent with mitigation of rollover risk and hedging motives, medium-term and long-term debt issues tend to be more pronounced for higher indebted governments. Moreover, as shown in Panel C of Table 2.1 displaying market characteristics, medium-term to long-term debt issues increase with a higher term structure of the yield curve. For example, the mean term premium is about 30bp higher for long-term debt issues compared to short-term debt issues. In contrast, theory predicts that a higher term premium should lead to reduced long-term debt issues in order to save interest expenditures, and this behavior is documented for example by Broner et al. (2013) for governments in emerging markets. Overall, these summary statistics suggest that while issuer characteristics appear to influence governments' maturity choice in line with theoretical predictions, the term structure might affect governments' maturity choice opposite to theoretical predictions.

To further investigate debt issuance behavior at the government-level, Panel A of Table 2.2 displays the frequencies of government debt issues across maturity buckets at the government-level. Consistent with the aggregated results discussed above, all governments issue the largest number of bonds in the short-term segment, but higher indebted governments such as Belgium, Greece and Portugal issue a relatively larger number of long-term bonds compared to lower indebted governments such as Finland and the Netherlands. Further, governments regularly issue debt as indicated by the high number of individual debt issues across governments. The median (mean) annual number of debt issues is 28 (46). To condense the maturity choice of governments at a quarterly frequency in line with governments' interval of maturity choice, I compute quarterly government-level shares of debt issues for each maturity bucket. This aggregation also accounts for variations in deal amounts across multiple debt issues within a quarter. On average, governments issue twelve bonds per quarter, but usually do not issue debt in each maturity bucket every quarter. Panel B of Table 2.2 reports the results of 3,645 government-quarter-maturity bucket observations, of which 2,014 are comprised of at least one debt issue (and 1,631 without any debt issue). On average, 50.54% of the total issuance amount is short-term. Also, and consistent with the larger deal amounts for long-term debt, 18.65% of the total debt issuance amount across all governments is on long-term debt issues (compared to 7.44% of the total number of long-term debt issues). Moreover, long-term debt issuances are clustered. On average, long-term debt issues occur only every second quarter, but once governments issue long-term debt, one fourth of issuance quarters contain more than half of the total quarterly debt issuance amount. In sum, long-term debt issues are a substantial part of governments' total debt issuances and vary substantially across governments and within governments over time.

2.4 Empirical analysis

2.4.1 Gap-filling debt maturity choice

In this section, I empirically test for gap-filling in the government bond market. According to gap-filling, governments' debt issues would fill supply gaps across maturities, which result from varying aggregate government funding patterns. As argued above, gap-filling should be more pronounced for governments long-term (greater than ten years) debt issues, because of higher duration risk capital for arbitrageurs and higher inelastic demand from life insurance and pension companies. The gap-filling hypothesis is therefore that governments increase their issuance of long-term debt following periods of low aggregate Eurozone government long-term debt issuance.

To test the gap-filling hypothesis, I investigate the determinants of governments' debt issuance across different maturity buckets. Specifically, I estimate Tobit models with the following latent variable regression

$$\begin{aligned} ShareIssue_{i,m,t} = & \alpha + \beta_1 \cdot AMT10_{t-1} + \beta_2 \cdot TermStructure10y6m_{i,t-1} \\ & \beta_3 \cdot Yield6m_{t-1} + \beta_4 \cdot SpreadToGermany10y_{i,t-1} \\ & + \gamma \cdot X_{i,t-1} + e_{i,m,t} \qquad \forall m \in M, \end{aligned} \tag{2.1}$$

where $ShareIssue_{i,m,t}$ is the share of debt issues of government i in quarter t in maturity segment m, which can be one of the five maturity buckets introduced above (with maturity ranges of (0,1] year, (1,3] years, (3,5] years, (5,10] years, and (10,...) years). The Tobit models take into account that the dependent variable is bounded between zero and one, and jointly estimates governments' decision to issue in a specific maturity segment as well as the issuance share. The key independent variable of interest is $AMT10_{t-1}$, which is the log of the aggregated Eurozone governments' long-term debt issue amount in the previous quarter. Consistent with the gap-filling hypothesis and governments' time interval of maturity choice, $AMT10$ is lagged by one period and therefore predetermined in period t, which suppresses contemporaneous issuance adjustments. Other country-specific credit market conditions are the slope of the government yield curve ($TermStructure10y6m_{i,t-1}$), the level of government short-term yields ($Yield6m_{i,t-1}$), and the long-term credit spread to Germany ($SpreadToGermany10y_{i,t-1}$), which are all lagged by one period consistent to governments' time interval of maturity choice. Further, $X_{i,t-1}$ contains a set of lagged country-level macroeconomic variables affecting governments' current maturity choice, such as the level of indebtedness, and the change in indebtedness over the previous four quarters. Standard errors are heteroscedasticity robust and clustered at the country-level.

Table 2.3 presents the set of Tobit model regression results. As shown, supply changes in aggregated Eurozone long-term debt affect governments' maturity choice non-linearly. Consistent with gap-filling, the coefficient estimate for AMT10 on long-term debt issues is negative and statistically significant at the 1%-level (see column (5)). Also, the coefficient for AMT10 on short-term debt issues is positive and statistically significant at the 1%-level (see column (1)), and both coefficient estimates of AMT10 are very similar in absolute magnitude. The coefficient estimate of AMT10 on debt issues in the remaining three maturity buckets is mostly close to zero and not statistically significant, besides for debt issues with (3,5] year maturities at the 10%-level. Consequently, governments engage in gap-filling by increasing long-term debt issues following periods of low aggregate Eurozone government debt, and vice versa.

Turning to other credit market conditions, I find that governments increase debt issues in the three intermediate maturity buckets during periods of a high term structure, while short-term debt issues are reduced (see columns (2)-(4)). This finding stays in contrast to theoretical models in which governments increase short-term issues in times of high term premia, when hedging fluctuating interest rates with long-term debt becomes more expensive (see for example Arellano and Ramanarayanan (2012)). An alternative explanation being consistent with my finding is that higher term premia stipulate increased investor demand for medium-term government debt, and governments cater this demand. Further, and consistent with only relative prices between short-term and long-term debt affecting governments maturity trade-off, the level of governments short-term yields does not affect short-term and long-term debt issues. Further, higher 10-year credit risk compared to Germany reduces governments' long-term debt issuance (see column (5)). This finding is consistent with investors reducing long-term funding to governments, when their credit quality deteriorates relative to Germany.

Also, the effects of macroeconomic conditions are broadly in line with theory. Consistent with theories of mitigating rollover risk, debt issues in the two maturity buckets greater than five years increase with the level of indebtedness (see columns (4) and (5)). Similarly, long-term debt issues increase (and short-term debt issues decrease) following positive changes in the level of governments' indebtedness. Conversely, deleveraging governments reduce long-term and increase short-term issuances, which is consistent with theories of incentivizing quicker paths to lower government debt levels (Aguiar et al. (2016)). In sum, I find strong evidence for governments' gap-filling and the effects of both credit market conditions and macroeconomic conditions are predominantly in line with theoretical predictions.

One concern of this gap-filling result might be that the dependent variable captures only the absolute share of debt issues, rather than temporary deviations. To alleviate this concern, I estimate OLS models of governments' debt issues across my five maturity buckets with different fixed effects.[12] For brevity, I only discuss the results here, but report the results for short-term and long-term debt issues in Table A. A.2.3 in the Appendix. In the different regression specifications, I sequentially include year, quarter, country-quarter, and country-year fixed effects to control for unobserved (country-level) time-invariant effects such as country-level specific issuance pattern, or (country-level) demand trends over time. Consistent with the Tobit model results, governments' gap-filling behavior continues to hold under all OLS model specifications. Specifically, the coefficient estimates of the AMT10 variable for long-term debt issues are negative, very similar in magnitude across all specifications, and also statistically significant at least at the 5%-level across all specifications (see Panel (b)). This gap-filling effect is also economically highly significant. A decrease from the 75th-percentile to the 25th-percentile of the AMT10 variable increases the share of governments' long-term debt issuance by between 5.04%-points to 6.55%-points across all specifications, which compares to a mean quarterly share of long-term debt issuance of 18.65%-points. Also consistent with the Tobit models results, governments' gap-filling results in a shift between long-term and short-term debt issues. The coefficient estimates on AMT10 for short-term debt issues are positive, similar in absolute economic magnitude than for long-term issues, and statistically significant at least at the 1%-level (besides for the most saturated specification being at the 5%-level) (see

[12] Even though the setup would continue to justify non-linear regression models, the incidental parameters problem in the Tobit model (see, e.g. Greene (2004)) justifies a linear model to include several fixed effects.

Panel (a)). In addition, as country-year fixed effects control for the stock of country-level long-term debt, my gap-filling result based on the flow of new debt issues can also be interpreted to hold for the stock of Eurozone government long-term debt. Overall, these results show the robustness of the gap-filling result and imply that governments' gap-filling constitutes a deviation from established debt issuance pattern.

2.4.2 Time-variation of gap-filling

In the previous subsection, I showed that governments engage in gap-filling debt maturity choice. Next, I analyze variations in governments' gap-filling over time. The theoretical gap-filling result from GHS (2010) builds on two key ingredients for governments' gap-filling: (1) partially segmented bond markets, and (2) limits to arbitrage. Partial segmentation of bond markets across maturities might have significantly increased since the start of harmonizing EU insurance regulation (Solvency II) on November 25, 2009, which reinforced insurers' incentive to match the maturity of its liabilities with government bonds. These matching incentives particularly affected life insurance companies' preferred habitat for long-term government debt, as matching the maturity of long-term liabilities is most efficient to reduce regulatory capital requirements. With insurance companies being the largest group of institutional investors in Europe with almost EUR 10 trillion of assets under management in 2014 according to Insurance Europe, these changed incentives might have significantly increased the segmentation of Eurozone government bond markets across maturities. In addition, limits to arbitrage might have increased over the same period as a result of banks reduced capitalizations due to the global financial crisis and Eurozone crisis, and tighter financial regulation in response to these crises.

To investigate possible variations in gap-filling over time, I use the start of harmonizing EU insurance regulation (Solvency II) as a cut-off to split the sample periods in two subperiods. Specifically, the first subperiod covers 1999 to 2009, and the second subperiod covers 2010 to 2015. Consistent with the gap-filling theory, I hypothesize that governments' gap-filling did not occur during the first subperiod with lower inelastic demand for long-term government debt and lower limits to arbitrage. Further, I conjecture that gap-filling occurred during the second subperiod with higher inelastic demand for long-term government debt and higher limits to arbitrage.

Table 2.4 provides estimates of Tobit models for short-term (up to one year) and long-term (greater than ten years) government debt issues for each subperiod. As hypothesized and shown in column (2), gap-filling did not occur during the first subperiod from 1999-2009. The coefficient estimate for AMT10 on long-term debt issues is close to zero and statistically insignificant.[13] Instead, governments reduced long-term debt issuance, when the level of short-term funding costs increased. That is, the coefficient estimate for the six-month government yield is negative and statistically significant at the 5%-level. However, and as hypothesized, governments engaged in gap-filling during the second subperiod from

[13] I also do not find governments' gap-filling in the subperiod from 2007:q2-2009:q4 covering lower capitalization of banks during the Global financial crisis.

2010-2015. The coefficient estimate for AMT10 on long-term debt issues is negative, almost double the magnitude compared to results across the entire sample period, and statistically significant at the 1%-level (see column (3)). In addition, the coefficient estimate of AMT10 on short-term debt issues is positive and statistically significant at the 1%-level (and the non-reported coefficient estimates of AMT10 for the three intermediate maturity ranges are close to zero and statistically insignificant).[14] Consequently, governments engage in gap-filling by shifting between long-term and short-term debt issuances, leaving intermediate maturity debt issues unchanged. In contrast to the first subperiod, long-term debt issuance is not affected by changes in the level of short-term yields. Instead, and consistent with catering investor demands, governments increase the issuance of long-term debt, when the term premium is high. Overall, these results show that gap-filling occurred only since 2010 and appears to be driven insurers inelastic demand for long-term government debt.

One concern might be that the gap-filling result in the 2010-2015 subperiod is driven by interactions in maturity choice between peripheral and core governments, for example as a result of peripheral governments reduced access to long-term funding during the Eurozone crisis. I counter this concern in two steps. First, I test governments' gap-filling behavior separate for core and peripheral governments over the entire 2010 to 2015 subperiod. Second, I estimate gap-filling across all governments after the Eurozone crisis (with a sample period from 2012:q4 to 2015:q3). For brevity, I discuss the results here and refer to Tables A. A.2.4 and A. A.2.5 in the Appendix. First, and similar to results for the 2010-2015 subperiod, both core and peripheral governments engaged in gap-filling behavior in the 2010 to 2015 period. The estimated coefficients on AMT10 for long-term debt issues are negative, very similar in magnitude between peripheral and core governments, and statistically significant at the 1%-level. Second, the gap-filling result also holds for the time-period after the Eurozone crisis. The coefficient estimate on AMT10 for long-term debt issues is negative, has very similar magnitude as in the other specifications and is statistically significant at the 1%-level. Overall, these results confirm the robustness of governments' gap-filling debt maturity choice in the 2010-2015 subperiod.

2.4.3 Cross-section of gap-filling

In the previous two sub-sections, I showed that governments engage in gap-filling, but only during the 2010-2015 subperiod. Next, I analyze for which types of governments gap-filling is more pronounced. As discussed above, gap-filling should be more pronounced for less financially constrained and higher rated governments. Less financially constrained governments might engage more aggressively in gap-filling, as they have higher flexibility to adjust the maturity structure of their debt issues (GHS (2010)). Higher rated governments might undertake gap-filling more aggressively, as investors prefer the high credit quality of government bond securities (KVJ (2012)).

To investigate cross-sectional variations, I estimate Tobit models of governments' long-

[14]These and all the following results are robust to excluding time periods affected by the introduction of the ECB's QE program in early 2015.

term debt issues across different subsamples of governments in the 2010-2015 subperiod. Governments' financial constraints are captured along five dimensions: indebtedness, size, funding needs, budget deficit, and future economic growth. Governments' credit quality is measured by its S&P's long-term local currency rating. Sample splits are defined as equal or above median within the same quarter (or year) in the panel of Eurozone governments, except for funding needs being defined within a government over time as specified in Ongena et al. (2016) and budget deficits are split above and below 3% corresponding to budget deficit limit in the Maastricht Criteria.

Table 2.5 shows estimates of Tobit models for long-term debt issues for subsamples of governments sequentially split across their indebtedness, size, funding needs, budget deficit, future economic growth, and rating. Consistent with theoretical predictions, I find that less financially constrained governments engage more aggressively in gap-filling. That is, governments' gap-filling is more pronounced when indebtedness is low, country size is small, funding needs are low, budget deficits are below the Maastricht criteria, and future economic growth is high (see columns (1), (3), (5), (7), and (9)). All coefficient estimates on AMT10 are negative, economically significant, and about three to four times (one half to one third higher than) the magnitude for more financially constrained governments across indebtedness and size (funding needs, budget deficit, and economic growth). These coefficient estimates on AMT10 are also statistically significant at the 1%-level, expect for funding needs at the 5%-level. Additionally, while less pronounced, gap-filling is still an important determinant of higher financially constrained governments' maturity choice. The coefficient estimate on AMT10 is negative, and statistically significant at least at the 5%-level for the subsamples of financially higher constraint governments (see columns (2), (4), (6), (8), and (10)). Consequently, less financially constrained governments possess a higher flexibility to issue their debt and possess a higher degree of freedom to structure their maturity profile of their outstanding debt.

Finally, and also consistent with theory, I find more pronounced gap-filling for higher rated governments. In the subsample of higher rated governments the coefficient estimate of AMT10 on long-term debt issues is negative, about one and a half times the magnitude for lower rated governments, and statistically significant at the 1%-level (see column (11)). The coefficient estimate on AMT10 on long-term debt issues for lower rated governments is also negative, and statistically significant at the 5%-level (see column (12)). Overall, I find that gap-filling is more pronounced for less financially constrained, and higher rated governments.

2.5 Event Study

Even though my government debt issuance data enables me to precisely capture governments' maturity choice that is consistent with gap-filling behavior, endogeneity problems from unobserved coordination of governments' debt maturity choice across countries remain. Specifically, individual governments might want to avoid concentrated maturity profiles of aggregated Eurozone government debt to mitigate rollover risk and limited access to capital market in case of a systematic shock to Eurozone governments (similar to Choi et al. (forthcoming)). Under this alternative explanation, changes in governments' debt maturity choice would be the result of coordinated supply, rather than a response to investor's maturity-specific demand. To address this concern, I exploit changes in peripheral governments' maturity choice (induced by peripheral banks' "carry trades") following the ECB's three-year long-term refinancing operations (LTRO) in 2011-2012 as a large, and largely unexpected negative credit supply shock of long-term government debt possibly affecting core governments maturity choice.

As discussed in detail below and illustrated in Figure 2, the ECB aimed to support bank lending and market liquidity when providing its largest liquidity provision ever to mostly weakly capitalized, peripheral banks. Peripheral banks used the ECB's liquidity to gamble for resurrection by entering into "carry trades" that matched the maturity of the ECB's three-year liquidity – that is, purchasing short-term peripheral government debt and depositing it as collateral at the ECB. As a response, peripheral governments increased short-term debt issuance to accommodate banks temporary collateral demand to mitigate their rollover risk during the Eurozone crisis. Given unchanged total debt issuance amounts, peripheral governments' adjustments in maturity choice induced a temporary negative credit supply shock of long-term Eurozone government debt. The corresponding gap-filling hypothesis is that core governments temporarily increased their issuance of longer maturity debt to fill this supply gap.

A concern might be that the ECB launched its large-scale liquidity provision to Eurozone banks to ease refinancing risks for peripheral governments during the escalation of the Eurozone crisis (in particular for non-EFSF/ESM program countries Italy, and Spain). However, Article 123 of the Treaty on the Functioning of the European Union (TFEU) prohibits the ECB from monetary financing of governments. In addition, even if the ECB might have intended that its large-scale liquidity provision improves peripheral governments refinancing conditions, the intervention is likely to be exogenous to core governments' maturity choices. Further, while financial market participants might have expected that the ECB lengthens its LTRO maturity compared to previous LTROs, the ECB's choice of granting liquidity for three years was still to a large degree incidental, and exogenous to core governments maturity choices. Consequently, the ECB's three-year LTRO constitutes a suitable event to investigate core governments' gap-filling behavior.

2.5.1 The ECB's three-year long-term refinancing operations

As a response to funding pressures of European banks caused by their exposure to risky Eurozone sovereign debt in the second half of 2011, the ECB announced on December 8, 2011 two unpreceded loans to banks in its three-year long-term refinancing operations (LTRO).[15] These three-year LTROs were an addition to the ECB's existing lending to

[15]The official ECB goal was to add "additional enhanced credit support measures to support bank lending and liquidity in the euro area money market." See

banks under its main refinancing operations (MRO). The three-year LTRO's conditions were equivalent to the ECB's MROs, except for granting liquidity for three years.[16] Specifically, the ECB's LTRO liquidity was granted unconditional to bank lending, the lending interest rates was floating at the MRO rate (tied to ECB policy rate), collateral and haircut conditions were more favorable than in the private markets, and lending was full allotment (no borrowing quantity limits for banks). These loan conditions were identical across all banks. As the ECB introduced full allotment in its MROs only in October 2008, uptake of the ECB's new three-year loans reduced banks uncertainty about potential future amount limits on the ECB MROs. In addition, both three-year loans included repayment options after one year, so that banks had flexibility about the duration of their ECB funding.[17]

Following the LTRO announcement, the ECB conducted two three-year LTRO allotments on December 21, 2011 (LTRO1), and on February 29, 2012 (LTRO2). Under LTRO1 523 banks borrowed EUR 489.2bn and under LTRO2 800 banks borrowed EUR 529.5bn. Banks were allowed to substitute new liquidity with existing ECB borrowing facilities (MROs, 3-month LTROs, 12-month LTRO[18]) so that in the week of LTRO1 the net increase in borrowing was EUR 210.0bn and in the week of LTRO2 the net increase in borrowing was EUR 310.6bn.[19] Yet, despite banks partial substitution of LTRO liquidity with existing ECB borrowing, the two LTRO loans significantly eased banks funding pressure and considerably reduced the uncertainty of banks funding due to the lengthened maturity. Consistent with the ECB's three-year LTRO being more favorable for weakly capitalized banks (see Drechsler et al. (2016)), banks in peripheral countries picked up more than two thirds of the total LTRO1 and LTRO2 loans.

2.5.2 Banks maturity-specific demand for government debt

The large-scale liquidity provision under the ECB's three-year LTRO allowed undercapitalized peripheral banks to gamble for resurrection by engaging in "carry trades" (e.g. Acharya and Steffen (2015)).[20] "Carry trades" constitute of purchasing high-yielding pe-

https://www.ecb.europa.eu/press/pr/date/2011/html/pr111208_1.en.html

[16]The MRO loan maturity is one week. Another type of prior ECB loans are LTRO loans with three month maturity.

[17]Banks aggregate repayments from January 25, 2013 to June 27, 2013 added up to 205.8bn EUR (101.7bn EUR) for the first (second) three-year LTRO, which is consistent to a substantial part of banks "carry trades" being conducted with short-term (up to one year) peripheral government debt issues. These debt issues accounted for the largest share of peripheral governments' debt issuance adjustments following the ECB's three-year LTRO as discussed in subsection 5.3 below. For details on LTRO repayments see https://www.ecb.europa.eu/pub/pdf/other/mb201307_focus04.en.pdf?33a710426a010fe7968e0adb8a0128 39

[18]The ECB allotted 3-month LTROs in April 2010, May 2010, and August 2011, and a 12-month LTRO in October 2011. Banks were allowed to switch liquidity from the 12-month LTRO with the three-year LTRO1 liquidity and shifted EUR 45.7bn.

[19]See https://www.ecb.europa.eu/mopo/pdf/mb201203en_box3.pdf?08c66bbcc045b15e9ae0e703851827 4d

[20]Peripheral banks' exposure to its domestic sovereign debt during the Eurozone crisis also increased due to "moral suasion" (see for example Ongena et al. (2016), and Altavilla et al. (2017)). However, the "moral suasion" channel - in comparison to the "carry trade" channel - is independent from the maturity structure of government bond purchases by banks.

ripheral government debt funded by cheap ECB funding, and depositing these peripheral government debt as collateral at the ECB. Purchasing bonds for "carry trades" with maturities of up to three years were particularly attractive to banks, as these matched the ECB funding maturity and consequently reduced banks liquidity and market risk (Crosignani et al. (2017)). While the yield spread on the "carry trades" was identical across all banks, incentives to engage in "carry trades" were very different between weakly capitalized banks in peripheral Eurozone countries and well-capitalized banks in core Eurozone countries. For weakly capitalized banks in peripheral Eurozone countries these "carry trades" were particularly attractive, as under-capitalized banks did not bear the entire downside risk of the trade due to the limited liability of equity. In addition, peripheral banks purchases of domestic peripheral government debt increased sovereign-bank linkages and consequently raised the likelihood of domestic bailouts of the banking system (Farhi and Tirole (forthcoming)). Consequently, "carry trades" allowed weakly capitalized peripheral banks to gamble for resurrection. In contrast, well-capitalized banks in core Eurozone countries were fully exposed to the downside risk of "carry trades" and their exposure to peripheral government debt did not affect their domestic bailout probability.

Table 2.6 reports country-level holdings of banks peripheral government debt holdings before and after the inception of the ECB's three-year LTRO. Changes in banks' peripheral government debt holdings between December 2011 and June 2012 are consistent with the above described asymmetric incentives for under-capitalized peripheral and well-capitalized core banks. Specifically, banks in peripheral Eurozone countries increased their holdings of GIIPS (Greece, Italy, Ireland, Portugal, and Spain) government debt (see also Crosignani et al. (2017)), while banks in core Eurozone countries reduced their holdings of GIIPS government debt. Also, increases by banks in peripheral countries are larger by a factor of six compared to decreases of banks in core countries, indicating that Eurozone banks in aggregate increased their demand for peripheral government debt. Consistent with peripheral banks "carry trades" demand, banks in peripheral Eurozone countries particularly increased their holdings of GIIPS government debt up to three years, while banks in core Eurozone countries reduced GIIPS government debt holdings similarly across maturities.

Further, changes in the slope of peripheral governments' yield curves following the announcement of the ECB's three-year LTRO are also consistent with a sharp increase in demand for shorter maturity peripheral government debt (see Figure 2.3, Panel A). The term premium – that is the difference between the 10-year yield and the 1-year yield – increased between the announcement of the ECB's three-year LTRO on December 8, 2011 and the second allotment on February 29, 2012 by 320bps for Italy, and 274bps for Spain, mainly resulting from reductions of the 1-year yield. Overall, both changes in banks holdings of peripheral government debt and changes in the slope of peripheral government yield curves following the announcement of the ECB's three-year LTRO indicate a large, and sudden increase in demand for short-term peripheral government debt.

In contrast, relative demand changes across maturities for Eurozone core governments rotated oppositely after the announcement of the ECB's three-year LTRO – indicating a sudden increase in the demand for longer maturity core government debt. Specifically, the term premia for core governments decreased between December 8, 2011 and February 29, 2012 – for example by 28bps for Germany, and 18bps for France – and continued to decline until the ECB president Draghi's "whatever it takes speech" on July 26, 2012 to a total of 72bps for Germany, and 57bps for France (see Figure 2.3, Panel B). In addition, rotating demand across maturities for core government debt is also observed in core governments' debt auctions. Excess demand (measured in the bid-to-cover ratio) in government debt auctions decreased for shorter maturities and increased for longer maturities for Germany and France during the LTRO-period (see Figure 2.4). In sum, after the announcement of the ECB's three-year LTRO demand for longer maturity core government debt increased significantly.

2.5.3 Governments' supply response

Next, I examine governments' response in their maturity choice of debt issues to the these changes in investor's maturity-specific demand for peripheral and core Eurozone government debt following the announcement of the ECB's three-year LTRO. As I will show below, peripheral governments accommodated peripheral banks "carry trade" demand for shorter debt maturities by reducing the supply of long-term debt. The corresponding gap-filling hypothesis is that core governments responded to this negative credit supply shock of long-term Eurozone government debt by filling the gap of longer maturity government debt.

In a first step, I analyze aggregate changes in the maturity structure of peripheral and core governments' debt issues in response to the ECB's three-year LTRO. Therefore, I compute the average maturity of all debt issues for both peripheral and core governments over time by weighting individual debt maturities by their notional issuance amount denominated in euro. Figure 2.5 shows that the average maturity of debt issues of peripheral and core governments shows a parallel trend before and after the LTRO-period, with core governments issuing debt with slightly shorter debt maturity compared to peripheral governments. However, during the LTRO-period the average maturity of debt issues diverged between peripheral and core governments. Consistent with peripheral governments accommodating peripheral banks demand for "carry trades", peripheral governments reduced their maturity of debt issues by 0.8 years to 2.6 years in the LTRO-period. Consistent with core governments' gap-filling of longer maturity government debt, core governments increased their average maturity of debt issues by 2.2 years to 5.1 years in the LTRO-period.

This rotation of peripheral and core governments' maturity structure of debt issues is also observed when analyzing the fraction of debt issues with maturities above three years over time (see Figure A. A.2.1 in the Appendix). Further and consistent my gap-filling results above, core governments decreased short-term (up to one year) debt issues to fill the gap of longer maturity government debt (see Figure A. A.2.2 in the Appendix).

In a second step, I investigate peripheral and core governments' maturity choices following the ECB's three-year LTRO in a regression setting. The baseline form of the regression I estimate is as follows:

$$\begin{aligned} ShareIssue_{i,m,t} = &\beta_1 \cdot Peripheral_i \cdot LTRO_t + \beta_2 \cdot Core_i \cdot LTRO_t \\ &+ \gamma \cdot X_{i,m,t} + e_{i,m,t} \qquad \forall m \in M \end{aligned} \tag{2.2}$$

The dependent variable $ShareIssue_{i,m,t}$ is the share of debt issues of government i in quarter t and maturity segment m, which can either be up to three years or greater than three years. These two maturity buckets are aligned according to the maturity of the ECB's three-year LTRO to reflect banks incentive to mitigate liquidity risk. The two key interaction terms in the regression are ($Peripheral_i \cdot LTRO_t$) and ($Core_i \cdot LTRO_t$). $Peripheral_i$ is an indicator variable equal to one if government i is a peripheral government, and $Core_i$ is an indicator variable equal to one if government i is a core government. $LTRO_t$ is an indicator variable equal to one if quarter t falls into the LTRO-period from 2012:q1 to 2012:q3. To ensure that peripheral governments' maturity choices are not affected by exclusion from capital markets and ongoing ESM-programs, I restrict peripheral governments to Italy and Spain. Core governments are Austria, Belgium, Finland, France, Germany, and the Netherlands, and the sample period is 2010:q1 to 2014:q3.[21] I further sequentially include different fixed effects, such as country, country-maturity, country-quarter, and maturity-quarter fixed effects. Standard errors are heteroscedasticity robust and clustered at the government level.

Table 2.7 reports the regression results. In all specifications, I find economically and at the 1%-level statistically significant coefficient estimates for changes of peripheral and core governments' maturity choices during the LTRO-period. That is, consistent with accommodating peripheral banks "carry trade" demand, peripheral governments increased their share of debt issues up to three years by 19.9%-points in the LTRO-period (the average share of debt issues up to three years is 52.3% outside the LTRO-period) (see column (1)). Correspondingly, peripheral governments' share of debt issues with maturities greater than three years reduced by 19.9% (see column (2)). Consistent with gap-filling, core governments increased their share of debt issues above three years by 14.5%-points in the LTRO-period (see column (2)). These maturity adjustments by core governments are equivalent to an increase of 44.8%, when compared to the mean share of debt issues greater than three years of 32.4%-points outside the LTRO-period. These regression results are also robust to sequentially including two-way fixed effects of country, maturity, and quarter.[22] Overall, this event study shows that core governments' gap-filling of longer

[21] This sample period is aligned to the gap-filling subperiod 2.4.2, but excludes periods affected by the introduction of the ECB's Q.E. program. The results shown below are robust to extending the sample period until 2015:q3.

[22] The results are also robust to analyzing governments' debt maturity choice at a monthly, or yearly frequency, and aggregating debt issues at the government-level in the pre-LTRO- and LTRO-period as

maturity debt is a response to investor's maturity-specific demand for government debt.

2.5.4 Financial implications of governments' supply response

The results above indicate that both peripheral and core Eurozone governments significantly altered their maturity structure of debt issues following the ECB's three-year LTRO. In this sub-section, I investigate the financial implications of these temporary maturity adjustments. Specifically, I focus government debt managers' primary maturity trade-off between funding needs and funding costs.

Figure 2.6 reveals that peripheral and core governments' temporary maturity adjustments following the ECB's three-year LTRO lead to a permanent effect on their overall debt maturity structures. The average residual maturity of total outstanding debt increased from 7.1 to 7.3 years across core governments and decreased from 6.8 to 6.4 years across peripheral governments from December 31, 2011 to September 30, 2012, while the average residual maturities show a parallel trend both before and after the LTRO-period. These maturity adjustments resulted in core governments' debt portfolios becoming less fragile due to lower future rollover requirements, while peripheral governments' debt portfolios became more fragile due to higher future rollover requirements.

To illustrate the effects on individual governments' debt rollover requirements, I next plot each government's debt maturity profile as at December 31, 2012. Therein, I highlight changes resulting from the introduction of the ECB's three-year LTRO. To compute the counterfactual – the debt maturity profile without the ECB's three-year LTRO effect –, I take a government's debt maturity profile as at December 31, 2011, and rescale the amount of debt issues in the LTRO-period to the maturity-bucket specific average share of debt issues from 2010 and 2011. The difference between the actual and counterfactual debt maturity profile is highlighted as the ECB's three-year LTRO effect.

Consistent with changes to the average residual maturity of total outstanding debt, I find that debt maturity profiles of peripheral governments shifted towards shorter maturities. In contrast, debt maturity profiles of core governments shifted towards long-term maturities. As shown in Figure 2.7, total debt rollover requirements until 2016 increased by 51.4bn EUR (or 3.3% of 2012 GDP) for Italy and 49.1bn EUR (4.7% of 2012 GDP) for Spain due to the ECB's three-year LTRO effect. Correspondingly, debt rollover requirements particularly for long-term debt (maturing after 2021) significantly reduced for Italy (30.1bn EUR) and Spain (50.0bn EUR). As shorter maturity debt is usually rolled over into debt with similar maturities, peripheral governments' debt rollover requirements are likely to increase also beyond 2016.

Consistent with gap-filling, debt maturity profiles of core governments' show that their increased debt issuance with maturities after 2021 filled the gap left by peripheral governments. In total, core governments increased their outstanding debt maturing after 2021 by 74.2bn EUR (or 1.1% of aggregated core governments 2012 GDP). Consequently,

suggested by Bertrand et al. (2004).

core government's gap-filling was almost euro-for-euro, replacing 93% (74.2bn EUR out of 80.1bn EUR) of the reduced long-term debt issuance by peripheral governments. Consistent with the gap-filling results across the longer time period above, core governments mainly reduced short-term debt issues maturing in 2013 by -52.6bn EUR (or -0.84% of aggregated core governments 2012 GDP).

Consistent with the cross-sectional results above, gap-filling was more pronounced for less financially constrained and higher rated governments. Finland as a AAA-rated, small, and lowly indebted country engaged most aggressively in gap-filling, increasing long-term debt issues maturing after 2021 by 4.2% of GDP. Austria as a AA+-rated, small, and then similarly indebted country as France and Germany increased long-term debt issues maturing after 2021 by 3.1% of GDP (compared to 0.8% of France (AA+-rated), and 0.9% of Germany (AAA-rated)). In sum, core governments' gap-filling lead to a permanent prolongation of their debt maturity profiles and consequently reduced future debt rollover requirements – particularly for less financially constrained and higher rated governments.

Finally, I investigate the effect of governments' adjusted debt maturity structure on governments funding costs. As yield curves were upward sloping in the LTRO-period (see Figure 2.3), peripheral governments might have significantly reduced their funding costs by increasing their issuance of shorter debt maturities. In contrast, core governments might have only possessed the ability to fill the gap of long-term bonds due to their capacity to pay higher funding costs.

Based on the same assumptions as for computing a governments' debt maturity profile without the ECB's three-year LTRO effect above, I also compute the resulting changes in governments' funding costs due to their maturity adjustments in the LTRO-period. My analysis reveals that core governments' gap-filling increased their funding costs by just 0.1bn EUR to 0.4bn EUR in 2012 (or between 0.01% to 0.12% of a core government's GDP), which compares to an average core government budget deficit of 2.9%. Consequently, core governments permanently lengthened their debt maturity profiles and reduced future debt rollover requirements at relatively low additional costs. Peripheral governments shift to shorter debt maturities reduced the funding costs for Italy and Spain by 1.1bn EUR (or 0.07% of GDP) and 0.5bn EUR (0.05% of GDP) in 2012, respectively. These funding costs reductions are also very small when compared to the Italy's and Spain's 2012 budget deficits of 2.9% and 10.4% of GDP, respectively. In sum, this evidence on changes in funding needs and funding costs is consistent with peripheral governments' main motive to adjust their debt maturity structure following the ECB's three-year LTRO being a temporary relief on debt rollover during the Eurozone crisis, despite its negative implications for future debt rollover requirements.

2.5.5 Robustness

Placebo test: ECB's first targeted long-term refinancing operation

A major concern of employing the ECB's three-year LTRO in 2011-2012 as an event study to investigate governments' gap-filling behavior might be confounding events during the Eurozone crisis. To alleviate this concern, I perform a placebo test based on another large-scale ECB liquidity provision dated after the Eurozone crisis. Specifically, I exploit the introduction of the ECB's first target long-term refinancing operations (TLTRO1) announced on June 5, 2014. The TLTRO1 intervention was very similar to the three-year LTRO, besides making liquidity provisions to banks conditional to bank lending.[23] This conditionality consequently also prohibited banks to use ECB liquidity for "carry trades", which induced peripheral governments to accommodate demand for shorter maturity peripheral government debt and subsequently led to core governments gap-filling following the ECB's three-year LTRO in 2011-2012. Another important difference is that in 2014 peripheral banks had a much higher level of capitalization, so that they would have been fully exposed to the downside risk of the "carry trades" compared limited downside risk following the three-year LTRO in 2011-2012. In addition, in 2014 peripheral sovereigns were more resilient compared to 2011-2012 so that increased bank-sovereign linkages would not have affected banks domestic bailout probability. In sum, the conditions that induced peripheral banks to engage in "carry trades" in 2011-2012 were largely eliminated by mid-2014. Consequently, I hypothesize that (peripheral) banks did not alter their demand for shorter maturity peripheral government debt following the inception of the TLTRO1 so that both peripherla and core Eurozone governments' maturity choices remained unaffected by the introduction of the TLTRO1.

Liquidity provisions under the ECB's TLTRO1 were allotted on eight allotments dates between September 24, 2014 to June 29, 2016, with the majority of the liquidity injection (384.1bn EUR out of 432.0bn EUR, or 88.9%) being allotted in the first four allotments until June 24, 2015.[24] All liquidity provisions matured on September 26, 2018 so that the loan maturity for the first four allotments amounted to four, or slighly below four years. Correspondingly, I use four years as the maturity cut-off between shorter and longer maturity debt and 2014:q4 to 2015:q3 as the TLTRO1-period (and a sample period from 2010:q1 to 2015:q3) for the placebo test.

Table 2.8 reports estimation results and shows that following the inception of the ECB's TLTRO1 program both peripheral and core governments maturity choice remained unchanged. Specifically, the magnitude of the estimated coefficients on the TLTRO1-period are close to zero and statistically insignificant for both peripheral and core governments' shorter and longer maturity debt issues (see columns (1), and (2)). These results also continue to hold when controlling for two-way fixed effects of country, maturity, and quarter. Correspondingly, liquidity allotments under the ECB's TLTRO1 did not affect peripheral and core governments maturity choices. Overall, this placebo test provides evidence that the ECB's three-year LTRO in 2011-2012 led to peripheral banks "carry trades", which resulted in peripheral governments accommodating their demand for shorter maturity debt and core governments to fill the gap of longer maturity debt.

[23] See https://www.ecb.europa.eu/press/pr/date/2014/html/pr140605_2.en.html

[24] See https://www.ecb.europa.eu/mopo/implement/omo/html/index.en.html

Restricted maturity choices for peripheral governments?
Another possible concern might be that investors restricted peripheral governments access to the longer maturity bond market by reducing their demand. Consequently, investors might have instead directly demanded core governments' longer maturity debt, rather than core governments filling the gap of longer maturity Eurozone government bonds.

Different pieces of evidence reject this concern. First, my analysis is restricted to Italy and Spain as peripheral governments, which had continuous access to the (longer maturity) bond market throughout the Eurozone crisis (compared to Greece, Ireland, and Portugal, which were partially excluded from financial markets). Second, during the LTRO-period, Italy and Spain issued on average 27.6% of their debt above three years every quarter, indicating that a substantial share of debt was refinanced with longer maturities. Third, excess demand for Italian and Spanish longer maturity bond auctions during the LTRO-period increased compared to the pre-LTRO period - indicating that investor's demand for long-term peripheral government debt remained unserved (see Figure 2.8). In sum, this evidence indicates that in the LTRO-period Italian and Spanish longer maturity debt issues were not restricted by investors.

Demand for safe assets
Another possible concern might be that investors demanded safe Eurozone government long-term assets during the acceleration of the Eurozone crisis. Consequently, investors might have predominantly demanded long-term government debt of Germany - rather than across all core governments - due to its relative safety, size and liquidity (He et al. (2016a), and He et al. (2016b)). Then, Germany's provision of safe long-term assets – rather than core governments' gap-filling – would have led to increased provision of long-term debt by core governments.

Different pieces of evidence reject this concern. First, investors increased their demand for longer maturity government debt similarly across all core governments, rather than exclusively for Germany. Yield curves for all core governments continuously flattened after the announcement of the ECB's three-year LTRO (see Figure 2.3), and increases in excess demand in longer maturity debt auctions were similar in France compared to Germany (see Figure 2.4). Second, all core governments – rather than exclusively Germany – increased their issuance of long-term debt in the LTRO-period (see Figute 2.7). Relative increases in the provision of long-term debt were even larger for Austria and Finland compared to Germany. These graphical observations are also confirmed in regression analyses, when estimating core governments gap-filling in the LTRO-period excluding Germany (see Table A. A.2.6 in the Appendix). The estimated regression coefficients for core governments increase in longer maturity debt issuance in the LTRO-period is almost identical in magnitude compared to the regression specification including Germany and statistically significant at the 5%-level. Overall, different pieces of evidence reject that demand for safe asset as the underlying channel for core governments increased provision of long-term government debt in the LTRO-period.

Deviations from debt issuance announcements

A final concern might be that observed changes in the maturity structure of debt issues following the three-year LTRO might have been the result of intended supply adjustments, rather than government's response to changes in investors' maturity-specific demand. To alleviate this concern, I analyze deviations between governments' announced and realized debt auctions. Based on expected demand by investors, governments publicly announce their planned future debt auctions. Nevertheless, governments also publicly communicate that they maintain the flexibility to deviate from their debt issuance announcements, if refinancing requirements or market conditions change. Consequently, deviations between governments' announced and realized debt auctions following the three-year LTRO identify supply adjustments caused by unexpected changes in investors' maturity-specific demand.

To compute deviations between governments' announced and realized debt auctions, I hand-collect data on debt auction announcements from Italy and Germany between 2010:Q1 and 2014:Q3. Representing both peripheral and core Eurozone governments, both countries frequently issue debt across the maturity spectrum and publicly provide detailed debt auction announcements around the ECB's three-year LTRO.[25] To obtain a matched data set of announced and realized debt auctions, I map announced debt auctions (via ISIN, auction date, and maturity date) to the corresponding realized debt auction. Then, I compute auction-level measures that relate realized debt auction amounts to announced amounts. Specifically, I compute the realized debt auction amount relative to the announced debt issues' minimum final outstanding amount for Italy, and relative to the announced debt auction target amount for Germany. Supply changes caused by investors changed maturity-specific demand are then identified based on realized debt auctions during the LTRO-period that were announced prior to the inception of the three-year LTRO. Consistent to the findings above, I hypothesize that Italy reduced issuance amounts of longer maturity debt auctions during the LTRO-period, while Germany increased issuance amounts of longer maturity debt auctions to fill the gap.

Table 2.9 provides evidence that peripheral governments catered investors' "carry trade" demand for shorter term maturities following the ECB's three-year LTRO and core governments filling the gap of longer maturity government debt. Italy reduced the amount of each longer maturity debt auctions by on average 11.07% (or EUR 1,220mn) of the announced minimum final outstanding debt issuance amount in the LTRO-period (column (2)). With a mean longer maturity debt auction amount of EUR 2,912mn, this adjustment is economically highly significant, and also statistically significant at the 1%-level. (The issuance amount of shorter maturity debt auctions also reduced, but fewer than for longer maturity debt auctions, while at the same time their frequency increased.) Further, Germany filled the gap of longer maturity Eurozone government debt by devi-

[25] Italy announces minimum final outstanding amounts of individual debt issues that are comprised of multiple debt auctions, while Germany announces target amounts of each individual debt auction.

ating from its debt issuance announcements. Specifically, Germany increased the amount of each longer maturity debt auction by on average 7.71% (or EUR 356mn) of the announced target amount in the LTRO-period (column (4)). With a mean longer maturity debt auction amount of EUR 3,710mn, his adjustment is economically highly significant, and also statistically significant at the 1%-level. Also, increases in debt auction amounts compared to pre-announced target amounts occurred exclusively for longer maturity bond auctions in the LTRO-period. Overall, these results investigating governments' deviations between announced and realized debt auctions are consistent to my previous findings and strengthen the identification of governments' gap-filling behavior.

2.6 Conclusion and policy implications

In this paper, I investigate whether gap-filling is also an important determinant of maturity choice in the government bond market. Consistent with gap-filling, I find that governments increase long-term debt issues following periods of low aggregate Eurozone government long-term debt issuance, and vice versa. This gap-filling behavior is more pronounced for (1) less financially constrained and (2) higher rated governments. I address endogeneity concerns in an event study using the ECB's three-year LTRO, and show that core governments filled supply gaps of longer maturity debt resulting from peripheral governments accommodating peripheral banks short-term debt demand for "carry trades". These maturity adjustments permanently stabilized core governments' debt portfolios, while it permanently increased the fragility of peripheral governments' debt portfolios.

My empirical findings have two important policy implications. First, Eurozone governments act as macro-liquidity providers across maturities, thereby providing significant risk absorption capacity to government bond markets. There is a widespread concern about deteriorated resilience in government bond market liquidity since the global financial crisis.[26] In contrast, governments' gap-filling behavior strengthens the resilience of government bond market liquidity. As ensuring market liquidity is important for the stability of the financial system and the transmission of monetary policy, governments' gap-filling might ultimately contribute to facilitating investments and economic growth in the real economy. Consequently, changes to the financial architecture, such as the creation of a safe government asset and the setup of a sovereign debt restructuring mechanism in the Eurozone, should be designed such that governments continue to be able to provide this risk absorption capacity.

Second, the gap-filling result from my event study of the ECB's three-year LTRO provides evidence for the interaction of unconventional monetary and fiscal policy. Specifically, ECB's large-scale liquidity provision to banks led Eurozone governments to adjust their maturity choices, which heterogeneously affected the stability of core and peripheral governments' debt portfolios. Consequently, being aware of governments' strategic debt

[26] See, for example, BIS (2016), ESRB (2016), and the testimony of the Federal Reserve System by Governor Jerome Powell (2016).

issuance responses to central banks' interventions in government bond markets might help to avoid unintended consequences of central bank interventions. Currently, these considerations appear of particular relevance for the discussion on the size and purpose of central banks asset holdings,[27] as well as central banks decisions on reducing their asset holdings, or tapering quantitative easing programs.

[27] For example, Greenwood et al. (2016) suggest that the Fed should permanently use its balance sheet to provide ample supply of government-provided short-term, safe instruments to improve financial stability.

2.7 Figures

Figure 2.1: Aggregated Eurozone Government Long-Term Debt Issue Amounts

This figure shows the aggregated debt issuance amounts of long-term debt issues by Eurozone governments from 1999:q1 to 2015:q3. Long-term debt issues have maturities greater than ten years. Foreign currency debt issuance amounts have been converted to euro.

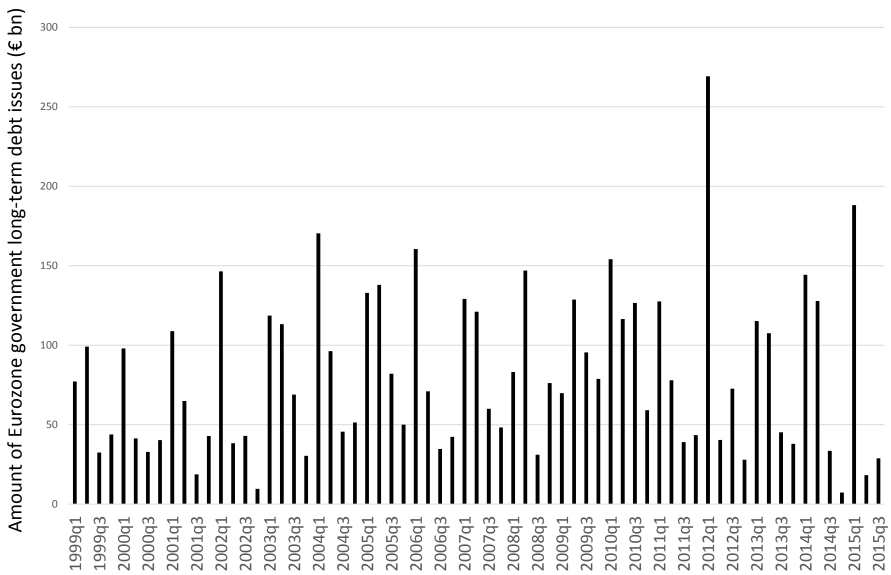


Figure 2.2: ECB's 3-Year LTRO as Negative Credit Supply Shock of Long-Term Debt

This figure illustrates the channels though which the ECB's three-year LTRO induced a negative credit supply shock to long-term Eurozone government debt.

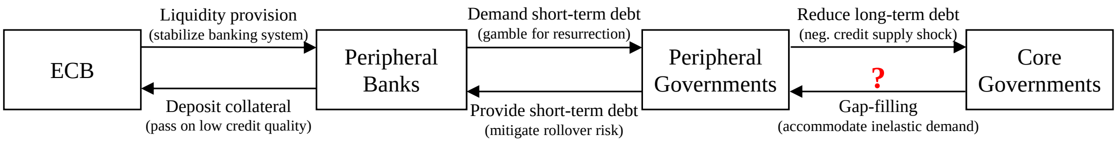
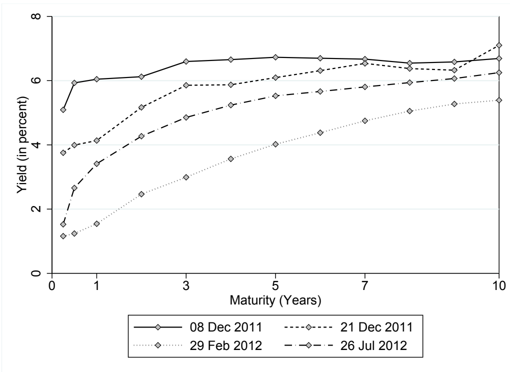


Figure 2.3: Changes in Government Yield Curves after the ECB's 3-Year LTRO

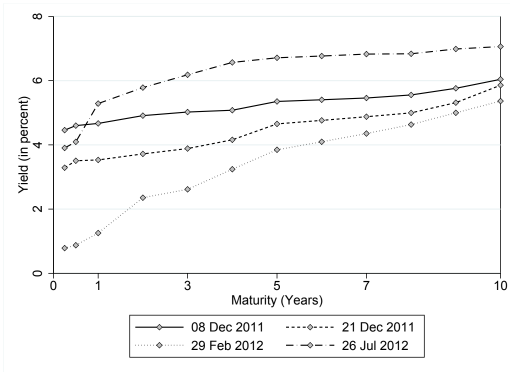
This figure shows snapshots from sovereign yields of peripheral and core governments at four points in time: December 8, 2011 (the announcement day of ECB's three-year LTRO), December 21, 2011 and February 29, 2012 (the two allotment days of the ECB's three-year LTRO), and July 26, 2012 (the day of ECB president Draghi's "whatever it takes" speech). The yield curves show yields of different maturities, ranging from three months to 10 years. Panel A shows the yields for peripheral countries, and Panel B for core countries. Yield data is obtained from Bloomberg.

Panel A: Peripheral Governments

(a) Italy

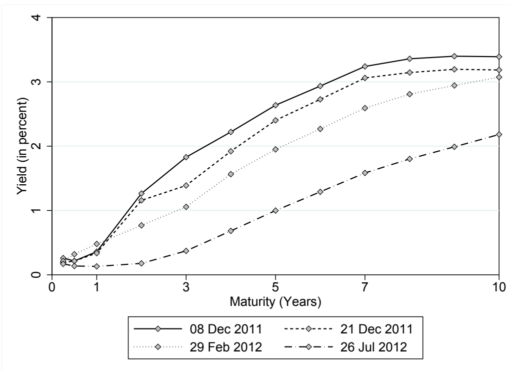


(b) Spain

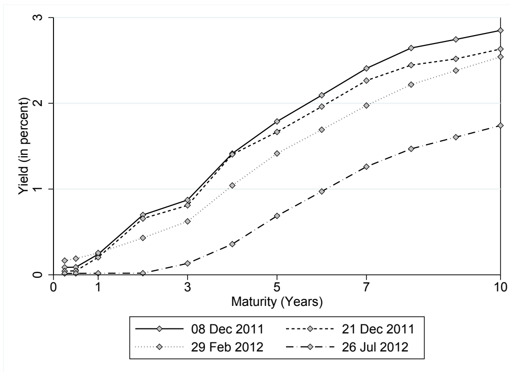


Panel B: Core Governments

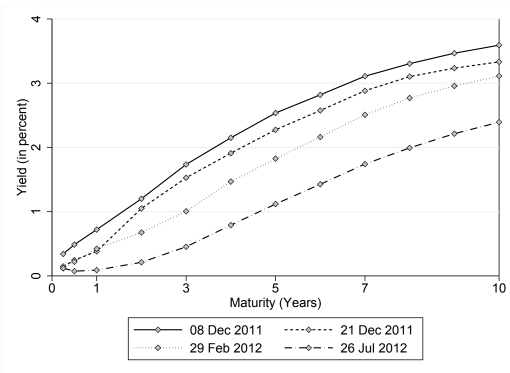
(c) Austria



(d) Finland



(e) France



(f) Germany

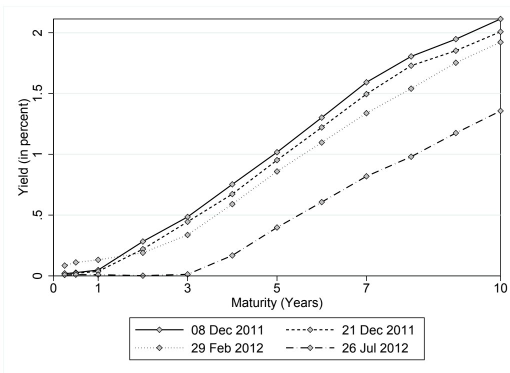


Figure 2.4: Excess Demand for Core Government Bonds Around ECB's 3-Year LTRO

This figure shows six-month moving averages of selected core governments bid-to-cover ratios of governments debt auctions of different maturities. The bid-to-cover ratio of an individual debt auction is computed as the aggregated bid amount over the total issuance amount. Selected core governments are France and Germany. Shorter maturity debt auctions have maturities of 0.5 years, and 1 year. Longer maturity debt auctions have maturities of 5 years, and 10 years. The grey shaded area depicts the LTRO-period from 2012:q1 to 2012:q3.

(a) Shorter maturity auctions (b) Longer maturity auctions

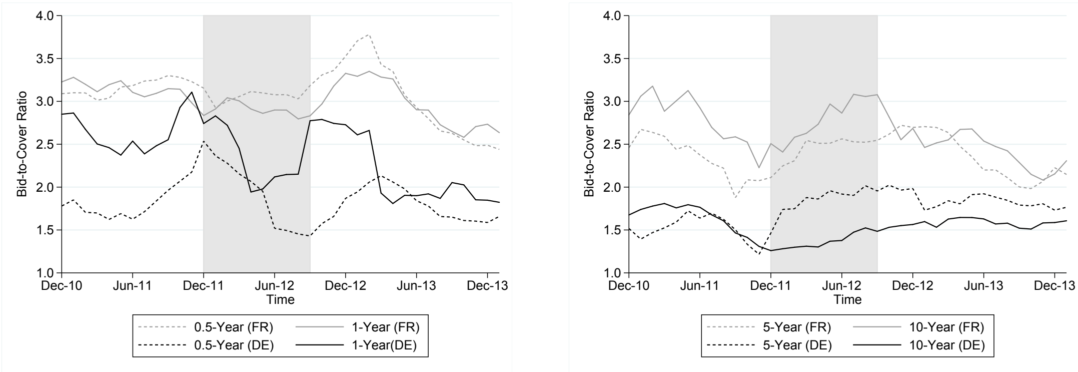


Figure 2.5: Avg. Maturity of Government Debt Issues Around ECB's 3-Year LTRO

This figure depicts the average maturity of debt issues by government groups around the ECB's three-year LTRO over time. The sample of governments is split into peripheral and core governments. The average maturity is computed as the mean of debt issues across all governments of the respective group. The grey shaded area depicts the LTRO-period from 2012:q1 to 2012:q3.

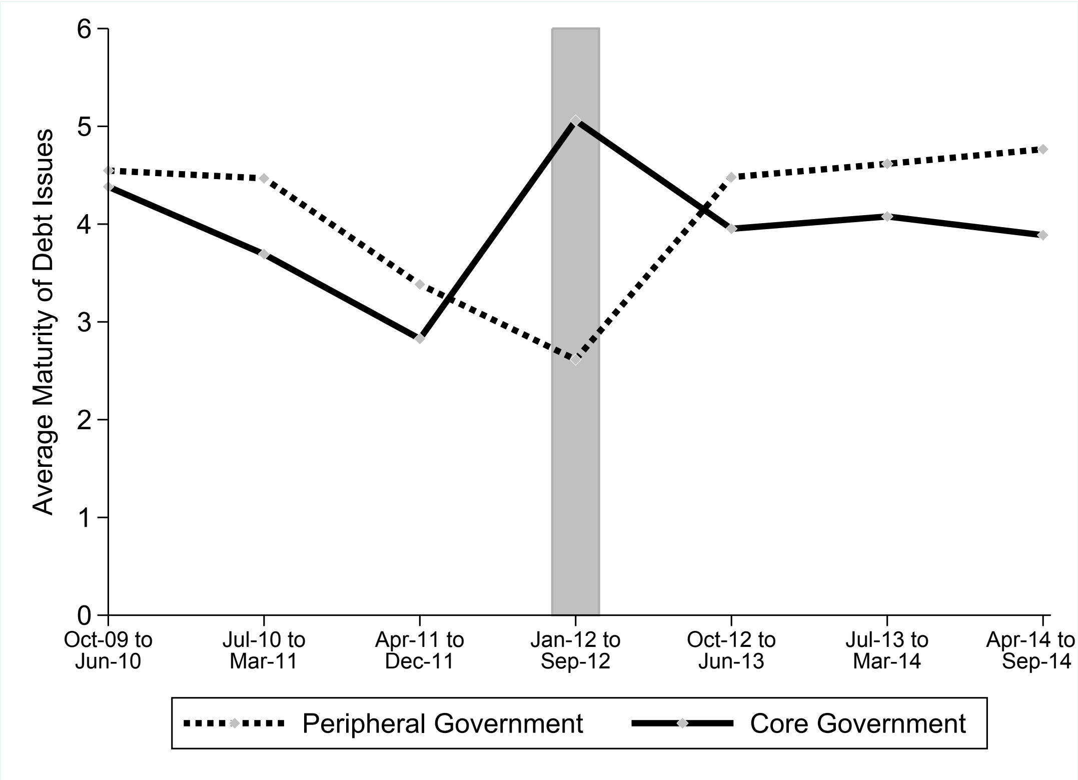


Figure 2.6: Avg. Residual Maturity of Outstanding Debt Around ECB's 3-Year LTRO

This figure shows the average residual maturity of outstanding debt around the ECB's three-year LTRO between December 31, 2010 and September 30, 2014. The sample of governments is split into peripheral and core Eurozone governments. The average residual maturity of outstanding debt is computed based on the residual maturity of all outstanding government bonds of a government group at a time, weighted by the bonds notional amount. The grey shaded area depicts the LTRO-period (2012:q1-2012:q3).

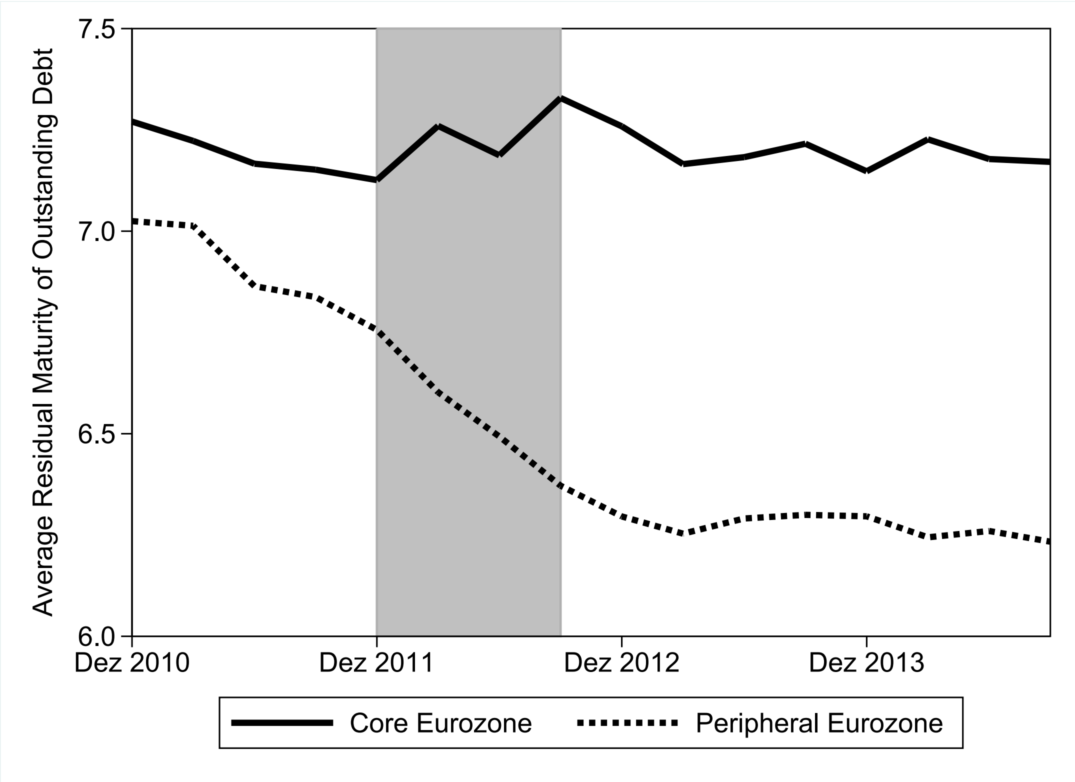
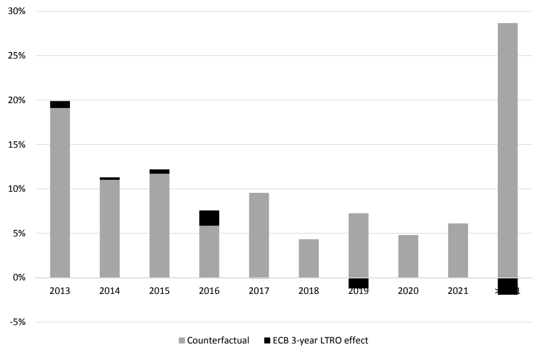


Figure 2.7: Debt Maturity Profiles and the ECB's 3-Year LTRO Effect

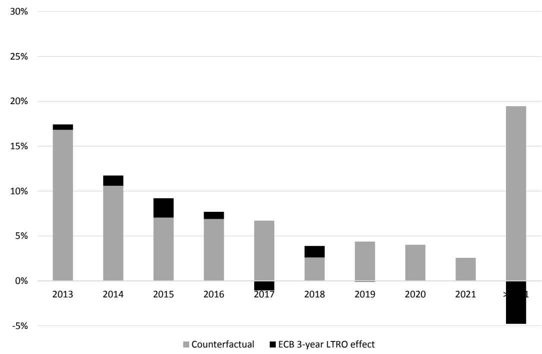
This figure shows the debt maturity profiles of Eurozone governments as at December 31, 2012. The changes resulting governments adjusted maturity choices following the introduction of the ECB's three-year LTRO are highlighted in black. To compute the counterfactual – that is the debt maturity profile without the ECB's three-year LTRO effect –, I take a government's debt maturity profile as at December 31, 2011, and rescale the amount of bond issues in the LTRO-period to the maturity-bucket specific average from the years 2010 and 2011.The difference between the actual and counterfactual debt maturity profile is highlighted as the ECB's three-year LTRO effect. Panel A shows peripheral governments, and Panel B shows core governments.

Panel A: Peripheral Governments

(a) Italy

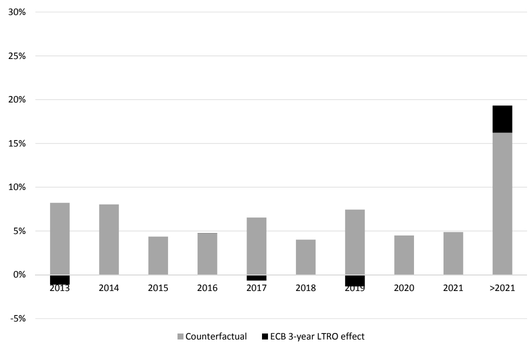


(b) Spain

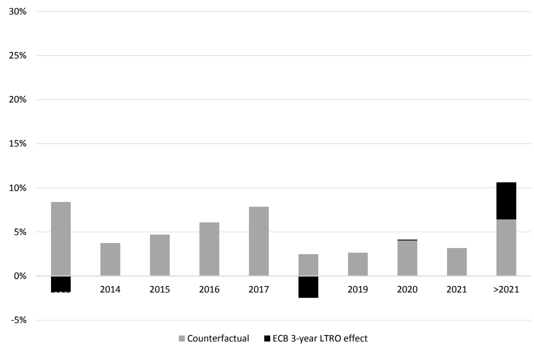


Panel B: Core Governments

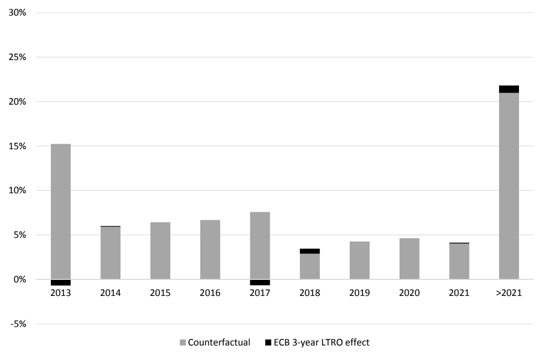
(c) Austria



(d) Finland



(e) France



(f) Germany

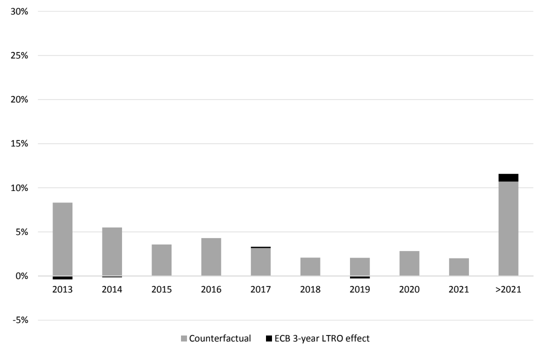
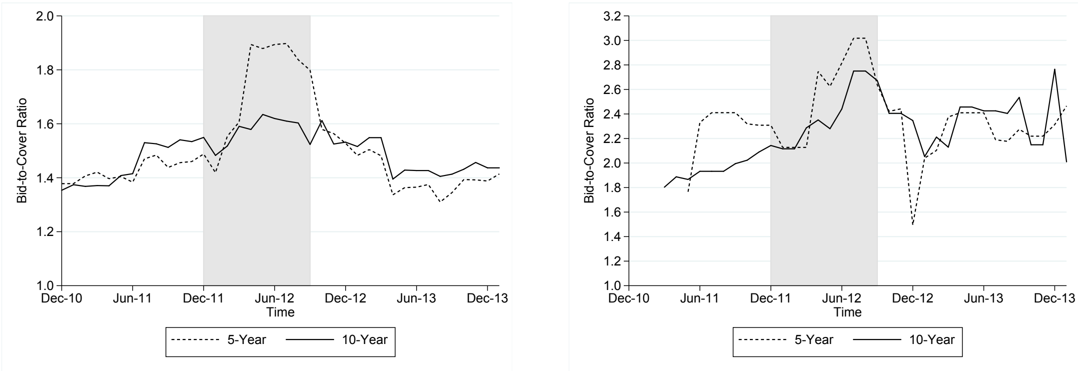


Figure 2.8: Excess Demand for Peripheral Gov. Bonds Around ECB's 3-Year LTRO

This figure shows six-month moving averages of two peripheral governments bid-to-cover ratios of governments longer maturity debt auctions. The bid-to-cover ratio of an individual debt auction is computed as the aggregated bid amount over the total issuance amount. The two peripheral governments are Italy and Spain. Bid-to-cover ratios of longer maturity debt auctions for maturities of 5 and 10 years are shown. The grey shaded area depicts the LTRO-period from 2012:q1 to 2012:q3.

(a) Longer maturity auctions (Italy) (b) Long maturity auctions (Spain)



2.8 Tables

Table 2.1: Summary Statistics by Maturity of Issue, 1999-2015

This table reports issuance-level summary statistics across the five different maturity buckets. The sample consists of all central government debt issuances by 15 Eurozone governments between 1999:q1 (or their year of joining the Eurozone) and 2015:q3 and is obtained from Bloomberg. Panel A reports summary statistics of individual debt issues. Panel B displays summary statistics of the issuing government at the time of issuance. Panel C reports credit market conditions of the government at the time of issuance.

	(0,1] Years			(1,3] Years			(3,5] Years			(5,10] Years			(10,...) Years		
	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median	N
Panel A: Deal Characteristics															
Years to Final Maturity	0.428	0.256	6,406	1.802	1.914	754	4.121	4.441	533	7.067	6.995	728	16.361	11.455	677
Deal Amount	2.052	0.192	6,406	4.985	2.284	754	3.695	0.728	533	4.359	0.240	728	8.194	2.480	677
Euro Denomination Dummy	0.688	1.000	6,406	0.786	1.000	754	0.636	1.000	533	0.777	1.000	728	0.873	1.000	677
Zero/Fixed Coupon Dummy	0.944	1.000	6,406	0.786	1.000	754	0.707	1.000	533	0.647	1.000	728	0.705	1.000	677
Not Inflation Linked Dummy	1.000	1.000	6,406	1.000	1.000	754	0.979	1.000	533	0.897	1.000	728	0.925	1.000	677
Repayment at Maturity Dummy	0.983	1.000	6,406	0.979	1.000	754	0.977	1.000	533	0.949	1.000	728	0.948	1.000	677
Panel B: Issuer Characteristics															
Non-IG Rating Dummy	0.017	0.000	6,341	0.004	0.000	747	0.002	0.000	533	0.011	0.000	723	0.007	0.000	667
Recession Dummy	0.122	0.000	6,406	0.155	0.000	754	0.182	0.000	533	0.115	0.000	728	0.093	0.000	677
Total GDP 4Q Growth	-0.002	-0.060	6,406	-0.342	-0.081	754	-1.066	-0.907	533	-0.323	-0.275	728	-0.067	-0.181	677
Inflation	1.875	1.868	6,406	2.251	2.239	754	2.136	2.230	533	1.914	1.953	728	1.795	1.932	677
Debt/GDP Ratio	0.548	0.524	6,406	0.530	0.471	754	0.554	0.498	533	0.565	0.524	728	0.611	0.587	677
Total Debt/GDP 4Q Change	0.030	0.024	6,389	0.027	0.017	753	0.041	0.031	532	0.030	0.023	727	0.028	0.022	675
Panel C: Market Characteristics															
AMT10	4.207	4.286	6,333	4.154	4.233	733	4.208	4.286	526	4.207	4.333	718	4.138	4.245	653
Termstructure 10y-6m	1.595	1.655	5,625	1.738	1.740	725	2.103	2.088	501	1.898	1.951	665	1.895	1.951	592
Yield 6m	2.613	2.744	5,625	2.793	3.010	725	2.226	2.133	501	2.404	2.143	665	2.067	2.138	592
Spread to Germany 10y	0.395	0.209	5,625	0.677	0.264	725	0.783	0.277	501	0.551	0.207	665	0.590	0.248	592

Table 2.2: Maturities by Government, 1999-2015

This table reports the distribution of debt issues by government and across maturity buckets. Panel A presents the frequencies of individual debt issues across 15 Eurozone governments between 1999:q1 (or their year of joining the Eurozone) and 2015:q3, which are obtained from Bloomberg. Panel B displays the mean quarterly share of debt issues across governments, which is computed based on the aggregation of individual debt issues' deal amounts within a government-quarter.

	(0,1] Years	(1,3] Years	(3,5] Years	(5,10] Years	(10,...) Years	Total
Panel A: Frequencies of Individual Debt Issues						
Austria	2,573	50	32	62	59	2,776
Belgium	227	29	56	102	76	490
Cyprus	115	5	9	9	2	140
Finland	368	41	40	25	15	489
France	1,186	67	47	168	105	1,573
Germany	249	67	12	46	46	420
Greece	93	3	18	22	34	170
Ireland	25	1	3	5	11	45
Italy	492	154	84	84	127	941
Malta	581	3	14	42	57	697
Netherlands	212	14	14	12	25	277
Portugal	43	13	5	9	19	89
Slovakia	12	2	5	13	12	44
Slovenia	119	7	7	9	8	150
Spain	111	298	187	120	81	797
Total	6,406	754	533	728	677	9,098
Panel B: Share of Debt Issues (quarterly, in percent)						
Austria	60.13	5.07	2.99	12.13	19.68	100.00
Belgium	66.34	8.07	1.97	6.35	17.28	100.00
Cyprus	67.87	5.75	19.44	6.43	0.51	100.00
Finland	56.09	5.61	10.03	12.83	15.45	100.00
France	67.00	4.96	3.47	7.90	16.68	100.00
Germany	30.97	26.53	3.39	18.26	20.86	100.00
Greece	31.88	2.91	16.09	19.91	29.21	100.00
Ireland	29.07	5.56	5.31	17.72	42.35	100.00
Italy	45.39	19.55	9.58	10.65	14.82	100.00
Malta	58.14	0.70	3.75	13.50	23.91	100.00
Netherlands	71.44	6.49	5.60	6.88	9.59	100.00
Portugal	44.67	11.62	4.18	12.12	27.41	100.00
Slovakia	30.03	1.14	9.83	29.63	29.36	100.00
Slovenia	56.42	9.35	7.11	10.71	16.41	100.00
Spain	18.70	36.08	12.50	12.49	20.23	100.00
Total	50.54	11.87	6.96	11.99	18.65	100.00

Table 2.3: Gap-Filling Government Debt Maturity Choice, 1999-2015

This table reports Tobit model regression results of governments share of debt issues across five maturity segments, on lagged AMT10 and control variables. The data sample is based on governments individual debt issues from 1999:q1 to 2015:q3 and is obtained from Bloomberg. The dependent variable is a governments' share of debt issues in a maturity segments (0,1], (1,3], (3,5], (5,10], and (10,...) years in a given quarter. The share of debt issues is computed as the aggregated issuance amount in the respective maturity segment over the total issue amount across maturity segments within a quarter. The Tobit model accounts for the share of debt issues being bounded between zero and one. AMT10 is the log of the aggregated amount of long-term (above 10 years) Eurozone government debt issues. Robust standard errors are reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	(1) (0,1] Y	(2) (1,3] Y	(3) (3,5] Y	(4) (5,10] Y	(5) (10,...) Y
model					
L.AMT10	0.096***	-0.024	-0.038*	-0.005	-0.085***
	(0.025)	(0.022)	(0.021)	(0.020)	(0.026)
L.Termstructure 10y-6m	-0.060**	0.051*	0.063***	0.055**	0.033
	(0.028)	(0.027)	(0.023)	(0.023)	(0.031)
L.Yield 6m	0.007	0.057***	0.007	0.002	-0.015
	(0.017)	(0.016)	(0.014)	(0.014)	(0.019)
L.Spread to Germany 10y	0.013	-0.013	-0.027	-0.002	-0.061**
	(0.026)	(0.025)	(0.018)	(0.025)	(0.027)
L.Non-IG Rating Dummy	0.095	-0.098	-1.564	-2.021	0.096
	(0.215)	(0.250)	(.)	(.)	(0.280)
Recession Dummy	0.061	0.027	-0.016	-0.086*	-0.032
	(0.056)	(0.047)	(0.043)	(0.049)	(0.067)
Total Real GDP Q4 Growth	-0.000	-0.006	-0.012*	0.009	0.005
	(0.010)	(0.008)	(0.007)	(0.009)	(0.012)
L.Inflation	-0.049***	0.012	0.028**	0.027**	-0.007
	(0.017)	(0.015)	(0.012)	(0.014)	(0.020)
L.Debt to GDP Ratio	0.147	-0.022	0.068	0.170**	0.209**
	(0.094)	(0.084)	(0.065)	(0.072)	(0.099)
Total Debt to GDP Q4 Change	-0.868***	-0.338	0.307	0.181	0.623*
	(0.294)	(0.284)	(0.240)	(0.252)	(0.346)
Constant	0.242*	-0.143	-0.150	-0.236**	0.255*
	(0.141)	(0.128)	(0.117)	(0.116)	(0.155)
sigma					
Constant	0.416***	0.346***	0.271***	0.326***	0.429***
	(0.015)	(0.018)	(0.022)	(0.016)	(0.019)
Onservations	625	625	625	625	625
Pseudo R^2	0.0435	0.0402	0.0738	0.0492	0.0314

Table 2.4: Time-Variation of Governments' Gap-Filling

This table reports Tobit model regression results of governments share of short-term (up to one year) and long-term (greater than ten years) debt issues across two subperiods, on lagged AMT10 and control variables. The data sample is based on governments individual debt issues from 1999:q1 to 2015:q3 and is obtained from Bloomberg. The two subperiods span from 1999:q1-2009:q4, and 2010:q1-2015:q3. The dependent variable is a governments' share of debt issues of (0,1] years, or (10,...) years of maturity in a given quarter. The share of debt issues is computed as the aggregated issuance amount of debt issues with maturities in the respective maturity range over the total issue amount across all maturities within a quarter. The Tobit model accounts for the share of debt issues being bounded between zero and one. AMT10 is the log of the aggregated amount of long-term (above 10 years) Eurozone government debt issues. Robust standard errors are reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	1999-2009		2010-2015	
	(1) (0,1] Y	(2) (10,...) Y	(3) (0,1] Y	(4) (10,...) Y
model				
L.AMT10	0.058*	-0.032	0.129***	-0.177***
	(0.033)	(0.037)	(0.038)	(0.040)
L.Termstructure 10y-6m	-0.051	-0.055	-0.064	0.143**
	(0.043)	(0.053)	(0.045)	(0.060)
L.Yield 6m	0.051	-0.091**	0.082	-0.077
	(0.035)	(0.043)	(0.050)	(0.068)
L.Spread to Germany 10y	0.059	-0.130	-0.048	-0.040
	(0.097)	(0.111)	(0.045)	(0.052)
L.Non-IG Rating Dummy			0.240	-0.049
			(0.222)	(0.279)
Recession Dummy	0.085	-0.033	0.008	0.013
	(0.073)	(0.084)	(0.108)	(0.124)
Total Real GDP Q4 Growth	-0.007	0.001	0.004	0.029
	(0.012)	(0.015)	(0.018)	(0.021)
L.Inflation	-0.073***	-0.004	-0.020	-0.001
	(0.024)	(0.025)	(0.029)	(0.038)
L.Debt to GDP Ratio	0.223*	0.148	0.126	0.248
	(0.119)	(0.130)	(0.163)	(0.160)
Total Debt to GDP Q4 Change	-1.258***	0.933*	-0.763	0.561
	(0.392)	(0.503)	(0.465)	(0.503)
Constant	0.247	0.438	0.134	0.347*
	(0.233)	(0.279)	(0.191)	(0.196)
sigma				
Constant	0.404***	0.426***	0.424***	0.408***
	(0.017)	(0.020)	(0.027)	(0.036)
Observations	409	409	216	216
Pseudo R^2	0.0566	0.0316	0.0687	0.1174

Table 2.5: Cross-Section of Governments' Gap-Filling, 2010-2015

This table reports Tobit model regression results of governments share of long-term (above 10 years) debt issues across different subsamples, on lagged AMT10 and control variables. The data sample is based on governments individual debt issues from 2010:q1 to 2015:q3 and is obtained from Bloomberg. The subsamples separate governments across indebtedness, size, funding needs, budget deficit, economic growth, and rating. The dependent variable is a governments' share of debt issues of (10,...) years of maturity in a given quarter. The share of debt issues is computed as the aggregated issuance amount of debt issues with maturities above 10 years over the total issue amount across all maturities within a quarter. The Tobit model accounts for the share of debt issues being bounded between zero and one. AMT10 is the log of the aggregated amount of long-term (above 10 years) Eurozone government debt issues. Robust standard errors are reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	Indebtedness		Size		Funding needs		Budget deficit		Economic growth		Rating	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	low	high	small	large	low	high	low	high	high	low	high	low
L.AMT10	-0.365***	-0.089**	-0.280***	-0.095***	-0.155**	-0.106**	-0.229***	-0.170***	-0.208***	-0.136**	-0.201***	-0.133**
	(0.097)	(0.044)	(0.086)	(0.028)	(0.074)	(0.051)	(0.070)	(0.052)	(0.051)	(0.063)	(0.053)	(0.055)
L.Termstructure 10y-6m	0.276*	0.067	0.307*	0.083**	-0.078	0.106	-0.011	0.217***	0.261***	0.057	0.120	0.146
	(0.140)	(0.059)	(0.162)	(0.035)	(0.096)	(0.080)	(0.108)	(0.076)	(0.078)	(0.081)	(0.078)	(0.103)
L.Yield 6m	-0.115	-0.089	-0.459**	0.025	-0.170	-0.099	-0.034	-0.077	-0.212**	0.026	-0.054	-0.028
	(0.173)	(0.064)	(0.183)	(0.050)	(0.131)	(0.073)	(0.123)	(0.087)	(0.092)	(0.084)	(0.091)	(0.103)
L.Spread to Germany 10y	-0.050	-0.003	-0.054	0.011	0.166	-0.047	0.040	-0.068	-0.037	-0.079	-0.011	-0.064
	(0.116)	(0.053)	(0.120)	(0.040)	(0.127)	(0.052)	(0.110)	(0.059)	(0.059)	(0.108)	(0.075)	(0.097)
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106	110	106	110	109	107	79	137	124	92	155	61
Pseudo R^2	0.1643	0.1159	0.1492	0.3225	0.1560	0.2130	0.1205	0.1609	0.2150	0.0871	0.1126	0.2311

Table 2.6: Gov. Debt Holdings of Eurozone Banks Around ECB's 3-Year LTRO

This table reports summary statistics of country-level government debt holdings for publicly listed banks in the Eurozone from the European Banking Authority (EBA) reported in Acharya and Steffen (2015). Panel A reports aggregate holdings in Irish, Italian, Portuguese, and Spanish government bonds of banks in GIIPS countries (GIIPS: Greece, Italy, Ireland, Portugal, and Spain) as of December 2011 and June 2012. Panel B reports changes in GIIPS government bond holdings by banks across different countries between December 2011 and June 2012 at the country level and by bond maturity ($\leq$ 3 years, $>$ 3 years). Changes in GIIPS government bond holdings of banks in core countries are also aggregated across countries. Core countries are Austria, Belgium, France, Germany, and the Netherlands.

	Panel A: GIIPS Sov. Bond Holdings (in EUR million)		Panel B: Change GIIPS Sov. Bond Holdings (in EUR million)	
	Dec 2011	Jun 2012	$\leq$ 3 years	$>$ 3 years
Ireland	10,487	11,938	1,511	119
Italy	153,923	189,508	27,355	7,261
Portugal	15,467	20,544	3,215	36
Spain	115,594	127,847	7,446	5,268
Core	N/A	N/A	-4,121	-4,731

Table 2.7: Gap-Filling by Core Governments at ECB's 3-Year LTRO

This table reports the estimates of the change in governments' debt maturity choices following the ECB's three-year LTRO announcement. The dependent variable in all specifications is the share of debt issues of maturity (range) m of country i in quarter t. The LTRO-period spans from 2012:q1 to 2012:q3. The first and second row test the changes in the share of short-term ($\leq$ 3 years) and long-term ($>$ 3 years) debt issues separately for core and peripheral countries and include country fixed effects. The third row tests the difference between the changes in the share of short-term ($\leq$ 3 years) and long-term ($>$ 3 years) debt issues separately for core and peripheral countries and includes country-maturity and country-time fixed effects. The fourth row tests the difference between core and peripheral countries difference between the changes in the share of short-term ($\leq$ 3 years) and long-term ($>$ 3 years) debt issues and includes country-maturity, country-time, and maturity-time fixed effects. Standard errors are clustered at the country level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	$ShareIssue_{i,short,t}$ (1)	$ShareIssue_{i,long,t}$ (2)	$ShareIssue_{i,m,t}$ (3)	$ShareIssue_{i,m,t}$ (4)
Peripheral × LTRO	0.199***	-0.199***	0.199***	0.242***
	(0.029)	(0.029)	(0.028)	(0.030)
Core × LTRO	-0.145***	0.145***	-0.145***	-0.103**
	(0.038)	(0.038)	(0.037)	(0.040)
Peripheral × Long × LTRO			-0.397***	-0.483***
			(0.056)	(0.059)
Core × Long × LTRO			0.290***	0.206**
			(0.075)	(0.079)
R-squared	0.227	0.227	0.344	0.434
Observations	151	151	302	302
Country FE	Yes	Yes		
Country-Maturity FE			Yes	Yes
Country-Quarter FE			Yes	Yes
Maturity-Quarter FE				Yes

Table 2.8: Placebo Test: No Gap-Filling at ECB's first Targeted LTRO

This table reports the estimates of the change in governments' debt maturity choices following the ECB's first four-year targeted (T)LTRO announcement. The dependent variable in all specifications is the share of debt issues of maturity (range) m of country i in quarter t. The TLTRO1-period spans from 2014:q4 to 2015:q3. The sample period end is extended by three quarters so that the entire sample perios spans from 2010:q1 to 2015:q3. The first and second row test the changes in the share of short-term ($\leq$ 4 years) and long-term ($>$ 4 years) debt issues separately for core and peripheral countries and include country fixed effects. The third row tests the difference between the changes in the share of short-term ($\leq$ 4 years) and long-term ($>$ 4 years) debt issues separately for core and peripheral countries and includes country-maturity and country-time fixed effects. The fourth row tests the difference between core and peripheral countries difference between the changes in the share of short-term ($\leq$ 4 years) and long-term ($>$ 4 years) debt issues and includes country-maturity, country-time, and maturity-time fixed effects. Standard errors are clustered at the country level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	$ShareIssue_{i,short,t}$ (1)	$ShareIssue_{i,long,t}$ (2)	$ShareIssue_{i,m,t}$ (3)	$ShareIssue_{i,m,t}$ (4)
Peripheral × TLTRO1	-0.012	0.012	-0.012	-0.019
	(0.052)	(0.052)	(0.051)	(0.052)
Core × TLTRO1	0.067	-0.067	0.067	0.059
	(0.038)	(0.038)	(0.037)	(0.037)
Peripheral × Long × TLTRO1			0.025	0.039
			(0.101)	(0.103)
Core × Long × TLTRO1			-0.134	-0.117
			(0.074)	(0.075)
R-squared	0.178	0.178	0.386	0.475
Observations	183	183	366	366
Country FE	Yes	Yes		
Country-Maturity FE			Yes	Yes
Country-Quarter FE			Yes	Yes
Maturity-Quarter FE				Yes

Table 2.9: Deviations from Debt Issuance Announcements after ECB's 3-Year LTRO

This table reports estimation results of linear regressions on issuance adjustments in government's debt auctions. Issuance adjustments are measured as the realized debt auction amount relative to the announced debt issues' minimum final outstanding amount for Italy (columns (1) and (2)), and relative to the announced debt auction target amount for Germany (columns (3) and (4)). Columns (1) and (3) provide results for multivariate regressions without fixed effects. Columns (2) and (4) provide results for multivariate regressions controlling for maturity segment, tranche, and quarter fixed effects. The relevant variables are indicator variables indicating whether a debt auction was announced prior to the inception of the ECB's three-year LTRO and auctioned during the LTRO-period for short-term (up to three years) and long-term (greater than three years) maturities. The bottom part of the table shows the hypothesis test (H_0: *LTRO x Long-Term – LTRO x Short-Term* = 0) and the hypothesis test's p-value. Robust standard errors are clustered at the maturity segment level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Italy: Measuring Issuance Adjustments Relative to Announced Minimum Total Debt Issue Amounts		Germany: Measuring Issuance Adjustments Relative to Announced Target Auction Amounts	
	(1)	(2)	(3)	(4)
	Realized over Announced Amount	Realized over Announced Amount	Realized over Announced Amount	Realized over Announced Amount
LTRO x Long-Term	-0.220***	-0.111***	0.089***	0.077***
	(0.024)	(0.022)	(0.019)	(0.020)
LTRO x Short-Term	-0.048	-0.080***	0.017***	0.012
	(0.025)	(0.005)	(0.004)	(0.008)
Maturity Segment F.E.		Yes		Yes
Tranche F.E.		Yes		Yes
Quarter F.E.		Yes		Yes
Observations	222	222	304	304
Adj. R^2	0.319	0.754	0.077	0.118
H_0	-0.171**	-0.030	0.072***	0.065**
p-value	0.002	0.320	0.007	0.018

2.9 Appendix

Figure A.2.1: Longer Maturity Debt Issues Around ECB's 3-Year LTRO

This figure shows the fraction of longer maturity debt issues around the ECB's three-year LTRO. Longer maturity debt issues are debt issues with maturities of (3,...) years. The sample of governments is split into peripheral and core Eurozone governments. Fractions are computed based on aggregated debt issuance amounts across governments within a government group with debt maturities above three years over total debt issuance amounts within the same group. Fractions are computed over the pre-LTRO- (2010:q1-2011:q4), LTRO- (2012:q1-2012:q3), and post-LTRO-period (2012:q4-2014:q3), respectively.

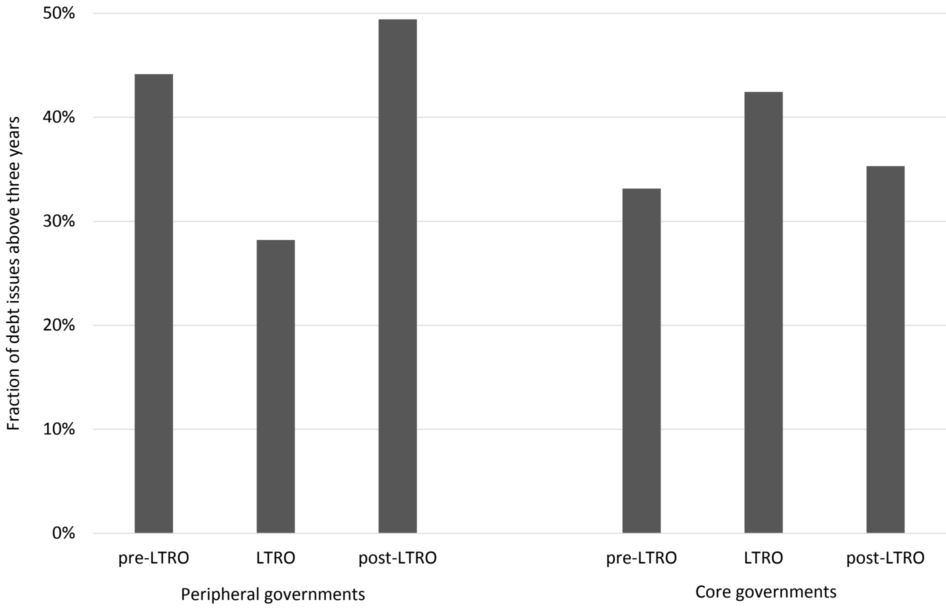
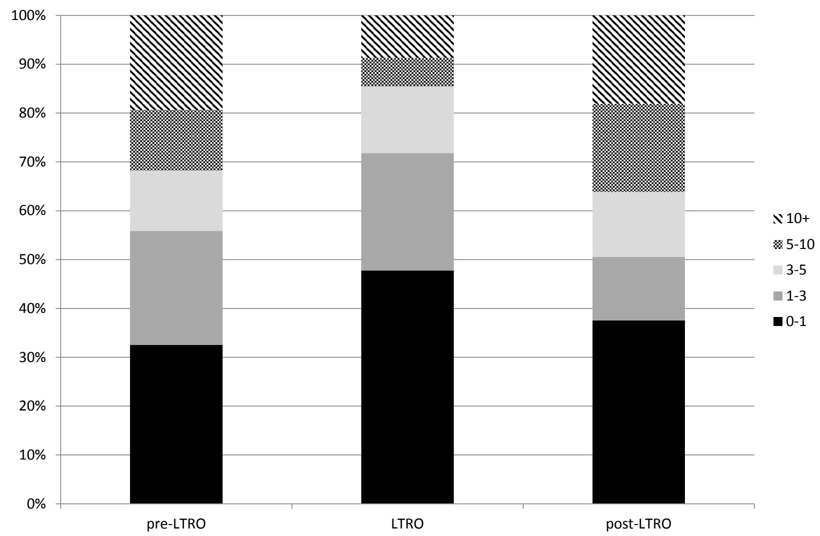


Figure A.2.2: Maturity Buckets of Debt Issues Around ECB's 3-Year LTRO

This figure shows the fraction of debt issues across five maturity buckets around the ECB's three-year LTRO. Debt issues are split into maturities of (0,1] year, (1,3] years, (3,5] years, (5,10] years, and (10,...) years. Panel A reports results for peripheral Eurozone governments, and Panel B for core Eurozone governments. Fractions are computed based on aggregated debt issuance amounts across governments within a government group with debt maturities in the respective maturity bucket over total debt issuance amounts within the same group. Fractions are computed over the pre-LTRO- (2010:q1-2011:q4), LTRO- (2012:q1-2012:q3), and post-LTRO-period (2012:q4-2014:q3), respectively.

(a) Peripheral Eurozone governments



(b) Core Eurozone governments

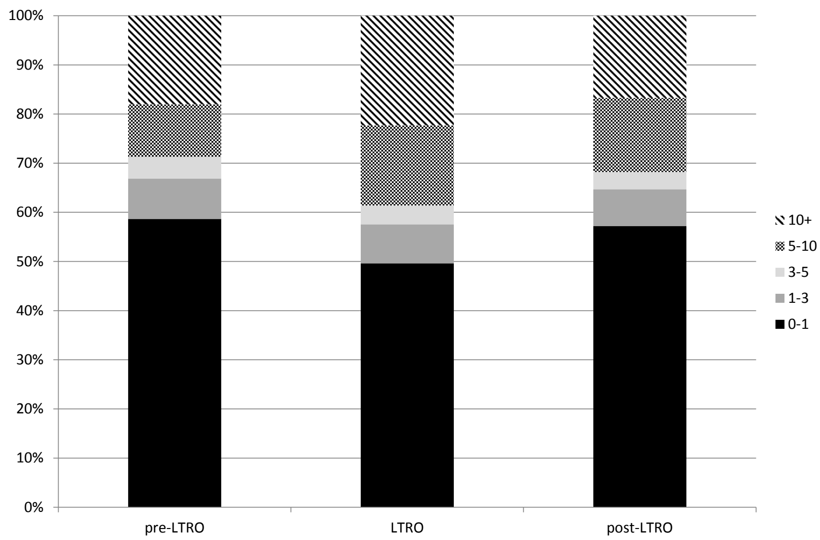


Table A.2.1: Description of Variables

The table describes all variables and their units of measurement. The variables are split in deal characterstics, issuer characteristics, and market characteristics.

Variable Name	Unit	Description
Panel A: Deal Characteristics		
Years to Final Maturity	Years	Years until final maturity of a debt issue.
Deal Amount	EUR bn	Notional issue amount in prices of 2010; converted to EUR at the exchange rate of the bond issue, if in non-EUR currency.
Euro Denomination Dummy	Dummy	Indicator variable; takes a value of one if debt is issued in EUR currency.
Zero/Fixed Coupon Dummy	Dummy	Indicator variable; takes a value of one if debt is issued as zero or fixed coupon bond.
Not Inflation Linked Dummy	Dummy	Indicator variable; takes a value of one if debt issue is not an inflation-linked security.
Repayment at Maturity Dummy	Dummy	Indicator variable; takes a value of one if debt issue repays at final maturity.
Panel B: Issuer Characteristics		
Qtly. Share of Debt Issues (0,1]Y	%	Quarterly amount of debt issues with maturities up to one year, over the total quarterly amount of debt issues.
Qtly. Share of Debt Issues (1,3]Y	%	Quarterly amount of debt issues with maturities greater than one year but not exceeding three years of maturity, over the total quarterly amount of debt issues.
Qtly. Share of Debt Issues (3,5]Y	%	Quarterly amount of debt issues with maturities greater than three years but not exceeding five years of maturity, over the total quarterly amount of debt issues.
Qtly. Share of Debt Issues (5,10]Y	%	Quarterly amount of debt issues with maturities greater than five years but not exceeding ten years of maturity, over the total quarterly amount of debt issues.
Qtly. Share of Debt Issues (10,...)Y	%	Quarterly amount of debt issues with maturities greater than ten years, over the total quarterly amount of debt issues.

Table A.2.1: Description of Variables
(continued)

Panel B: Issuer Characteristics		
Non-IG Rating Dummy	Dummy	Indicator variable; takes a value of one if the government has a long-term local-currency credit rating by S&P of BBB- or higher.
Recession Dummy	Dummy	Indicator variable; takes a value of one if the governments last two consecutive quarters had negative GDP growth.
Total GDP 4Q Growth	%	The Countries growth in real GDP during the past four quarters.
Inflation	%	The Countries consumer price inflation (CPI) during the prior twelve month.
Debt/GDP Ratio	Ratio	The countries total government debt over GDP of the previous year.
Total Debt/GDP 4Q Change	Ratio	The total change in the governments' debt/GDP ratio in the previous four quarters.
Peripheral × LTRO	Dummy	Interaction term of indicator variable "Peripheral" that takes a value of one if the country is Italy or Spain; and the indicator variable "LTRO" that takes a value of one if the quarter is included in the ECB's LTRO-period from 2012:q1 to 2012:q3.
Core × LTRO	Dummy	Interaction term of indicator variable "Core" that takes a value of one if the country is Austria, Belgium, Finland, France, Germany, the Netherlands; and the indicator variable "LTRO".
Peripheral × Long × LTRO	Dummy	Interaction term of indicator variable "Peripheral", "Long" that takes a value of one for the share of debt issues with maturities above three years, and "LTRO".
Core × Long × LTRO	Dummy	Interaction term of indicator variable "Core", "Long" and "LTRO".
Peripheral × TLTRO1	Dummy	Interaction term of indicator variable "Peripheral" and the indicator variable "TLTRO1" that takes a value of one if the quarter is included in the ECB's TLTRO1 period from 2014:q4 to 2015:q3.

Table A.2.1: Description of Variables
(continued)

Panel B: Issuer Characteristics		
Core × TLTRO1	Dummy	Interaction term of indicator variable "Core" and the indicator variable "TLTRO1".
Peripheral × Long × TLTRO1	Dummy	Interaction term of indicator variable "Peripheral", "Long" and "TLTRO1".
Core × Long × TLTRO1	Dummy	Interaction term of indicator variable "Core", "Long" and "TLTRO1".
Panel C: Market Characteristics		
AMT10	Log (EUR bn)	Natural logarithm of the sum of deal amounts of Eurozone government debt issues with maturities above ten years.
Termstructure 10y-6m	%	Difference between the percentage yields of 10-year and 6-month government securities.
Yield 6m	%	The percentage yield of 6-month government securities.
Spread to Germany 10y	%	The Difference between the percentage yields of 10-year government securities and 10-year German government securities.

Table A.2.2: Government Debt Managers in the Eurozone

The table reports the debt managers of Eurozone governments in the sample. Information on debt managers include the name, institutional position within the government, and website.

Country	Debt Manager	Institutional position	Website
Austria	Österreichische Bundesfinanzagentur	Part of the Ministry of Finance	www.oebfa.at/en
Belgium	Agence Fédérale de la Dette/Federaal Agentschap van de Schuld	Part of the Federal Public Service Finance	www.debtagency.be/en
Cyprus	Public Debt Management Office	Part of the Ministry of Finance	www.mof.gov.cy/mof/pdmo/pdmo.nsf/index_en/index_en
Finland	Valtiokonttori	State Treasury responsible to the Ministry of Finance	www.statetreasury.fi/en-US
France	Agence France Trésor	Part of the Ministry of the Economy and Finance	www.aft.gouv.fr/
Germany	Bundesrepublik Deutschland - Finanzagentur GmbH	Limited company with the Federal Republic of Germany, represented by the Federal Ministry of Finance, as sole shareholder	www.deutsche-finanzagentur.de/en
Greece	Public Debt Management Agency	Board of Directors is appointed by the Minister of Finance, Agency responsible to the Ministry of Finance	www.pdma.gr/en
Ireland	National Treasury Management Agency	Chairperson is appointed by the Minister of Finance, Agency responsible to the Ministry of Finance	www.ntma.ie
Italy	Dipartimento del Tesoro	Part of the Ministry of Economy and Finance	www.dt.tesoro.it/en/
Malta	Debt Management Directorate	Part of the Treasury Department	treasury.gov.mt/en
Netherlands	Agentschap van de Generale Thesaurie	Part of the Ministry of Finance	english.dsta.nl
Portugal	Agência de Gestão da Tesouraria e da Dívida Pública - IGCP, E.P.E.	Agency supervised by the Finance Minister	www.igcp.pt/en
Slovakia	Agentúry pre riadenie dlhu a likvidity	Agency responsible to the Ministry of Finance	www.ardal.sk/en
Slovenia	Ministrstvo za finance	Part of the Ministry of Finance	www.mf.gov.si/en
Spain	Tesoro Público	Part of the Ministry of Economy, Industry and Competitiveness	www.tesoro.es/en

Table A.2.3: Gap-Filling Government Debt Maturity Choice (OLS Models), 1999-2015

This table reports OLS model regression results of governments share of short-term and long-term debt issues, on lagged AMT10 and control variables. The data sample is based on governments individual debt issues from 1999:q1 to 2015:q3 and is obtained from Bloomberg. The dependent variable is a governments' share of debt issues in the short-term maturity segments of (0,1] years, and the long-term maturity segments of (10,...) years in a given quarter. The share of debt issues is computed as the aggregated issuance amount in the respective maturity segment over the total issue amount across maturity segments within a quarter. AMT10 is the log of the aggregated amount of long-term (above 10 years) Eurozone government debt issues. Panel A reports results for short-term debt issues, and Panel B reports results for long-term debt issues. Heteroscedasticity-robust and clustered standard errors at the government-level are reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

(a) Short-Term Debt Issues

	(1) (0,1] Y	(2) (0,1] Y	(3) (0,1] Y	(4) (0,1] Y	(5) (0,1] Y	(6) (0,1] Y
L.AMT10	0.078***	0.070***	0.069***	0.073***	0.075***	0.071**
	(0.023)	(0.022)	(0.019)	(0.018)	(0.020)	(0.027)
L.Termstructure 10y-6m	-0.036	-0.065	0.009	0.030	0.017	0.010
	(0.033)	(0.061)	(0.055)	(0.053)	(0.056)	(0.057)
L.Yield 6m	0.010	0.042	0.117*	0.088	0.080	0.087
	(0.020)	(0.064)	(0.060)	(0.052)	(0.052)	(0.053)
L.Spread to Germany 10y	-0.007	-0.034	-0.107*	-0.084	-0.078	-0.117
	(0.030)	(0.059)	(0.055)	(0.051)	(0.049)	(0.112)
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	
Quarter FE			Yes	Yes		Yes
Country FE				Yes		
Country-Quarter FE					Yes	
Country-Year FE						Yes
Observations	625	625	625	625	625	625
R^2	0.0671	0.0989	0.1635	0.3925	0.4966	0.5557

(b) Long-Term Debt Issues

	(1) (10,...) Y	(2) (10,...) Y	(3) (10,...) Y	(4) (10,...) Y	(5) (10,...) Y	(6) (10,...) Y
L.AMT10	-0.047**	-0.054***	-0.058***	-0.057***	-0.061***	-0.059**
	(0.017)	(0.017)	(0.013)	(0.013)	(0.013)	(0.021)
L.Termstructure 10y-6m	-0.002	0.061	0.011	0.004	0.022	-0.006
	(0.013)	(0.041)	(0.038)	(0.042)	(0.045)	(0.052)
L.Yield 6m	-0.012	0.007	-0.042	-0.039	-0.035	-0.034
	(0.009)	(0.036)	(0.030)	(0.027)	(0.028)	(0.037)
L.Spread to Germany 10y	-0.017	-0.037	0.012	-0.015	-0.018	-0.016
	(0.016)	(0.042)	(0.038)	(0.041)	(0.043)	(0.084)
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	
Quarter FE			Yes	Yes		Yes
Country FE				Yes		
Country-Quarter FE					Yes	
Country-Year FE						Yes
Observations	625	625	625	625	625	625
R^2	0.0302	0.0655	0.1376	0.1718	0.3051	0.3288

Table A.2.4: Gap-Filling by Government Group, 2010-2015

This table reports Tobit model regression results of governments share of debt issues across five maturity segments for different government groups, on lagged AMT10 and control variables. The data sample is based on governments individual debt issues from 2010:q1 to 2015:q3 and is obtained from Bloomberg. The dependent variable is a governments' share of debt issues in a maturity segments (0,1], (1,3], (3,5], (5,10], and (10,...) years in a given quarter. The share of debt issues is computed as the aggregated issuance amount in the respective maturity segment over the total issue amount across maturity segments within a quarter. The Tobit model accounts for the share of debt issues being bounded between zero and one. AMT10 is the log of the aggregated amount of long-term (above 10 years) Eurozone government debt issues. Panel A reports results for peripheral governments, and Panel B reports results for core governments. Robust standard errors are reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

(a) Peripheral Governments

	(1) (0,1] Y	(2) (1,3] Y	(3) (3,5] Y	(4) (5,10] Y	(5) (10,...) Y
L.AMT10	0.194***	-0.043	0.041	-0.030	-0.198***
	(0.051)	(0.043)	(0.034)	(0.047)	(0.048)
L.Termstructure 10y-6m	-0.061	0.079	0.037	-0.011	0.005
	(0.091)	(0.071)	(0.053)	(0.070)	(0.075)
L.Yield 6m	0.064	0.072	-0.009	-0.075	-0.098
	(0.075)	(0.068)	(0.055)	(0.078)	(0.086)
L.Spread to Germany 10y	0.034	-0.069	-0.046	0.039	-0.082
	(0.068)	(0.046)	(0.044)	(0.071)	(0.064)
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes
Observations	73	73	73	73	73
Pseudo R^2	0.2772	0.2981	0.6184	0.2368	0.2803

(b) Core Governments

	(1) (0,1] Y	(2) (1,3] Y	(3) (3,5] Y	(4) (5,10] Y	(5) (10,...) Y
L.AMT10	0.091*	0.012	0.002	-0.001	-0.163***
	(0.051)	(0.040)	(0.052)	(0.044)	(0.058)
L.Termstructure 10y-6m	-0.030	0.016	0.035	-0.010	0.223**
	(0.064)	(0.065)	(0.060)	(0.056)	(0.087)
L.Yield 6m	0.145	-0.067	0.060	0.014	-0.250**
	(0.117)	(0.093)	(0.094)	(0.100)	(0.117)
L.Spread to Germany 10y	-0.077	-0.342**	-0.030	0.063	0.098
	(0.076)	(0.152)	(0.068)	(0.079)	(0.096)
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes
Observations	143	143	143	143	143
Pseudo R^2	0.0577	0.2189	0.0296	0.0657	0.1168

Table A.2.5: Gap-Filling After the Eurozone Crisis, 2012:q4-2015:q3

This table reports Tobit model regression results of governments share of debt issues across five maturity segments, on lagged AMT10 and control variables. The data sample is based on governments individual debt issues following the Eurozone crisis (from 2012:q4 to 2015:q3) and is obtained from Bloomberg. The dependent variable is a governments' share of debt issues in a maturity segments (0,1], (1,3], (3,5], (5,10], and (10,...) years in a given quarter. The share of debt issues is computed as the aggregated issuance amount in the respective maturity segment over the total issue amount across maturity segments within a quarter. The Tobit model accounts for the share of debt issues being bounded between zero and one. AMT10 is the log of the aggregated amount of long-term (above 10 years) Eurozone government debt issues. Robust standard errors are reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	(1) (0,1] Y	(2) (1,3] Y	(3) (3,5] Y	(4) (5,10] Y	(5) (10,...) Y
model					
L.AMT10	0.133***	-0.013	-0.032	0.023	-0.170***
	(0.048)	(0.039)	(0.050)	(0.046)	(0.050)
L.Termstructure 10y-6m	-0.012	-0.007	0.065	0.079	-0.006
	(0.091)	(0.071)	(0.077)	(0.085)	(0.118)
L.Yield 6m	0.193	0.071	-0.058	-0.023	-0.410**
	(0.145)	(0.130)	(0.104)	(0.144)	(0.160)
L.Spread to Germany 10y	-0.155	0.026	-0.008	0.038	0.172
	(0.112)	(0.098)	(0.097)	(0.110)	(0.138)
L.Non-IG Rating Dummy	0.445*	-0.147	-1.938	-2.547	-0.114
	(0.243)	(0.252)	(.)	(.)	(0.310)
Recession Dummy	0.104	0.008	-0.028	-0.174	-0.006
	(0.173)	(0.077)	(0.123)	(0.117)	(0.184)
Total Real GDP Q4 Growth	0.055	-0.014	-0.112***	-0.021	0.029
	(0.037)	(0.023)	(0.039)	(0.036)	(0.037)
L.Inflation	0.094	-0.046	-0.189***	-0.022	0.040
	(0.082)	(0.051)	(0.067)	(0.084)	(0.102)
L.Debt to GDP Ratio	0.510*	0.229	-0.129	-0.093	0.333
	(0.275)	(0.198)	(0.212)	(0.300)	(0.290)
Total Debt to GDP Q4 Change	-0.575	-0.416	0.405	-0.400	0.352
	(0.782)	(0.607)	(0.822)	(0.857)	(0.935)
Constant	-0.309	-0.206	0.127	-0.164	0.335
	(0.286)	(0.205)	(0.266)	(0.276)	(0.310)
sigma					
Constant	0.425***	0.309***	0.299***	0.373***	0.431***
	(0.037)	(0.043)	(0.053)	(0.036)	(0.055)
Observations	110	110	110	110	110
Pseudo R^2	0.1028	0.1022	0.2174	0.1029	0.1400

Table A.2.6: Gap-Filling by Core Gov. (excluding Germany) at ECB's 3-Year LTRO

This table reports the estimates of the change in governments' debt maturity choices following the ECB's three-year LTRO announcement, excluding Germany as core government. The dependent variable in all specifications is the share of debt issues of maturity (range) m of country i in quarter t. The LTRO-period spans from 2012:q1 to 2012:q3. The first and second row test the changes in the share of short-term ($\leq$ 3 years) and long-term ($>$ 3 years) debt issues separately for core and peripheral countries and include country fixed effects. The third row tests the difference between the changes in the share of short-term ($\leq$ 3 years) and long-term ($>$ 3 years) debt issues separately for core and peripheral countries and includes country-maturity and country-time fixed effects. The fourth row tests the difference between core and peripheral countries difference between the changes in the share of short-term ($\leq$ 3 years) and long-term ($>$ 3 years) debt issues and includes country-maturity, country-time, and maturity-time fixed effects. Standard errors are clustered at the country level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Dependent Variable	$ShareIssue_{i,short,t}$ (1)	$ShareIssue_{i,long,t}$ (2)	$ShareIssue_{i,m,t}$ (3)	$ShareIssue_{i,m,t}$ (4)
Peripheral × LTRO	0.199***	-0.199***	0.199***	0.237***
	(0.029)	(0.029)	(0.028)	(0.030)
Core × LTRO	-0.150**	0.150**	-0.150**	-0.114**
	(0.046)	(0.046)	(0.045)	(0.046)
Peripheral × Long × LTRO			-0.397***	-0.473***
			(0.056)	(0.060)
Core × Long × LTRO			0.300**	0.227**
			(0.090)	(0.093)
R-squared	0.233	0.233	0.353	0.447
Observations	132	132	264	264
Country FE	Yes	Yes		
Country-Maturity FE			Yes	Yes
Country-Quarter FE			Yes	Yes
Maturity-Quarter FE				Yes

Chapter 3

Banks' interconnectedness through syndicated corporate loan portfolios – impact on bank-level systemic risk

3.1 Introduction

The financial crisis of 2007-2009 demonstrated how large risk spillovers among financial institutions caused a global systemic crisis and worldwide economic downturn. The collapse of the interbank market at the beginning of the crisis suggests that direct linkages between banks are an important channel of contagion across financial institutions (Allen and Gale (2000); Allen and Babus (2009), Gorton and Metrick (2012); Giglio (2016)). A second channel that explains how shocks propagate through financial systems is information contagion (Chen (1999)). A third important channel is commonality of asset holdings. As banks have similar exposure to assets such as syndicated loans, a decline in asset prices can affect the banking system because of direct exposure of banks to the same assets as well as fire sale externalities (e.g. Shleifer and Vishny (1992, 2011); Kiyotaki and Moore (1997)). Common exposures of banks are of first order importance as indicated by Federal Reserve Chairman Bernanke in his speech at the Conference on Bank Structure and Competition in May 2010 in Chicago:[1]

[1] Common exposures have played an important role in various historical crises: The Savings & Loans crisis in the U.S. in the 1980s was caused by maturity mismatch of the asset and liability side of banks' balance sheets and a shock to (i.e., increase of) interest rates (Ho and Saunders (1981)). The Asian financial crisis in the 1990s was associated with exchange rate risks. The recent crises in Ireland and Spain were associated with a decline in real estate prices. The 2007-2009 financial crisis involved a decline in real estate prices as well as various forms of contagion magnifying the extent of the crisis (Hellwig (2014), Hellwig (1995)).

"We have initiated new efforts to better measure large institutions' counterparty credit risk and interconnectedness, sensitivity to market risk, and funding and liquidity exposures. These efforts will help us focus not only on risks to individual firms, but also on concentrations of risk that may arise through common exposures or sensitivity to common shocks. For example, we are now collecting additional data in a manner that will allow for the more timely and consistent measurement of individual bank and systemic exposures to syndicated corporate loans."

In this paper, we study interconnectedness in the form of common exposures among financial institutions examining banks' exposure to large syndicated loans. The syndicated loan market provides an ideal laboratory to study interconnectedness of banks. It is the most important funding source for non-financial firms (Sufi (2007)), and banks repeatedly participate in syndicated loans arranged by one another. We know borrower and lender identities and are thus able to track banks' investments in this market to quantify common risk exposures.

To measure commonality in banks' syndicated loan portfolio, we develop a novel measure of interconnectedness for which the key component is the similarity between two banks' syndicated loan portfolios.[2] The similarity is measured as the Euclidean distance between two banks based on their exposures to specific borrower industries or regions in the prior twelve months. We then aggregate the distance of one bank with all other banks in each month and construct our bank-level interconnectedness measure using three different weighting schemes: (1) equal weights for each bank, (2) size weights to account for the fact that larger banks might contribute more to systemic risk, and (3) relationship weights to capture prior contractual relationships between banks. Equal weights are used a benchmark against which we evaluate the effect of size and relationships.

We document a high propensity of bank lenders to concentrate syndicate partners rather than to diversify them, as lead arrangers are more likely to collaborate with banks with similar corporate loan portfolios. We then investigate the determinants of interconnectedness both cross-sectionally and over time. While bank size explains only between 5% and 16% of the variation in interconnectedness in the cross-section in univariate tests (depending on the type of exposure and weighting scheme), we document that diversification explains between 61% and 96% of this variation. Overall, our results suggest that bank size is not a first order determinant of interconnectedness but highlights the importance of banks' diversification motive in understanding interconnectedness in the syndicated loan market.

Recent theoretical work has shown that interconnectedness can increase systemic risk through various forms of financial contagion because of common exposures in times of crises (Allen et al. (2012a); Castiglionesi and Navarro (2010); Ibragimov et al. (2011);

[2] For example, Abbassi et al. (2017) apply our distance measure to German banks lending portfolios to explain market-based risk measures.

Wagner (2010)).[3]

The first channel relies on direct linkages between banks. Once a bank defaults it can propagate stress to other creditor banks (Allen and Gale (2000)).[4] A second important channel is information contagion (Chen (1999)). If one bank is in distress, investors reassess the risk of other institutions that they believe have similar exposures. Short-term investors may decide not to roll over their investments if solvency risks are high but engage in precautionary liquidity hoarding (Acharya and Skeie (2011)). A third channel is commonality of asset holdings. Shocks can propagate through fire sales when banks need to sell assets to reduce their leverage. (Shleifer and Vishny (1992, 2011)).[5]

The time-series evolution of our interconnectedness measure is consistent with interpretation of elevated systemic risk through contagion arising from common exposures. We aggregate the bank-level interconnectedness measure to a market interconnectedness index in each month and document that the benchmark equally-weighted interconnectedness index is persistently lower compared to indexes using the size- and relationship-weighting schemes. This is an important finding. For example, the size-weighted index is larger compared to the equally-weighted one which suggests that banks have greater overlap with larger banks consistent with the literature on bank moral hazard and herding behavior (e.g. Acharya and Yorulmazer (2008))and banks exploiting government guarantees (e.g. Eisert and Eufinger (2017)).

In the final part of the paper, we relate our interconnectedness indexes to different measures of systemic risk. Similar to approaches used in stress tests that have been conducted in the U.S. and Europe since 2008, the construction of these measures is to estimate losses in a systemic stress scenario and determine a bank's equity shortfall after accounting for these losses. These measures capture asset price as well as funding liquidity risks associated with interconnectedness using market data (Acharya et al. (2014)).

We employ three frequently used bank-level systemic risk measures: (1) systemic capital shortfall (SRISK) (Acharya et al. (2017); Brownlees and Engle (2017)), (2) distressed insurance premium (DIP) (Huang et al. (2009)), and (3) conditional value-at-risk (CoVaR) (Adrian and Brunnermeier (2016)).[6] All three concepts measure a co-movement of equity or credit default swap (CDS) prices without the notion of causality, i.e. a bank can contribute to systemic risk of the financial system because it initiates a contagious event or because of its exposure to a common factor. Moreover, all measures are constructed to estimate cross-sectional differences in systemic risk at a point in time.

[3] Wagner (2010) shows that diversification increases systemic risk also in the absence of contagion. While diversification reduces the risk of failure of an individual bank, it also increases the likelihood that they default jointly. Moreover, banks can diversify not only in different industries and regions, but also in different sectors (Acharya et al. (2006)) such as sovereign debt or household debt which we cannot do due to data limitations.

[4] Allen et al. (2009), Diebold and Yilmaz (2014), Gorton and Metrick (2012), Duffie (2014) and Giglio (2016) provide further discussions.

[5] Fire-sale amplifications are also discussed in, for example, Kiyotaki and Moore (1997), Brunnermeier and Pedersen (2009), Allen et al. (2012a) and Greenwood et al. (2015).

[6] Other market-based measures (e.g., based on stock return volatility) are developed in Diebold and Yilmaz (2014), Diebold and Yilmaz (2015), Billio et al. (2012) and Hautsch et al. (2015).

We find a positive and significant correlation between our interconnectedness measure and SRIK, but only during recessions. A one standard deviation increase in interconnectedness increases SRISK by almost one-third relative to the average SRISK. Intuitively, a large shock to the market amplifies the effect of interconnectedness if banks are more vulnerable during recessions. Similarly, we find that interconnectedness increases DIP, but also only during recessions. The economic magnitude is comparable, i.e. a one standard deviation increase in interconnectedness increases DIP by about one-third. Bank size is an important determinant of both SRISK and DIP.

We also find that interconnectedness is positively related to CoVaR during recessions. In contrast to the effect of interconnectedness on SRISK, the effect is somewhat smaller. A possible reason is that CoVaR measures the increase in systemic risk of the market when an individual bank is in distress. During recessions, when the market is already weak, the marginal impact of an increase in bank risk is small.

Overall, our bank level tests suggest a positive and significant correlation between our interconnectedness measure and various systemic risk measures including SRISK, DIP, and CoVaR.[7] Controlling for bank and loan market size as well as various fixed effects we show that, consistent with the theoretical papers cited above, interconnectedness amplifies systemic risk during recessions when asset commonality can cause various forms of contagion such as fire-sales.[8] Another way of interpreting this result is that interconnectedness of banks – that builds up during normal times - is a useful tool to forecast cross-sectional differences in banks' contribution to systemic risk if a severe crisis occurs. Various tests suggest that our results are consistent across different systemic risk measures and model specifications. Consequently, our results highlight that institution-level risk reduction through diversification ignores the negative externalities of an interconnected financial system.

While syndicated loan market exposures reflect, on average, only a percentage of banks' balance sheets, large exposures are of systemic relevance for several reasons. First, the syndicated loan market is extremely large with an annual issuance volume of more than $1,000 billion in the U.S.; markets in Europe and Asia are large as well. As has been documented earlier (e.g., Sufi (2007)), virtually all publicly listed firms use this market to finance working capital and for other corporate or capital structure related purposes. Second, individual loans are quite sizeable, too, with respect to a bank's asset size and equity capital.[9] Moreover, banks are financed to some extent with short-term debt instruments and therefore face the risk of bank runs. Additionally, banks' behavior in the syndicated

[7] We also show in an Online Appendix a positive and significant link between our interconnectedness measure and the market based CATFIN measure developed by Allen et al. (2012b).

[8] In contrast, Sedunov (2016) proxies a bank's interconnectedness with aggregate measures of loans and derivative positions to other financial institutions – without distinguishing between recession and expansion periods – and finds no effect of interconnectedness on bank-level systemic risk measures.

[9] On average, the ratio of syndicated corporate loans originated during a 12-months period as a percentage of bank total assets is 9.6%. Other factors need to be considered as well: For example, suppose that book equity is about 5% or less relative total assets, then syndicated loans on a bank's balance sheet is eventually twice a bank's book equity.

loan market can be used to estimate their systemic risk preferences (Gong and Wagner (2016)). Banks want to be correlated with other institutions and interconnectedness in the syndicated loan market can be used to measure these preferences that extend to other asset classes of banks' balance sheets.[10]

The paper proceeds as follows. In Section 3.2, we describe the empirical methodology, in particular, derive our measures of distance and interconnectedness, and discuss various systemic risk measures as well as the related literature. Data are described in Section 3.3. Sections 3.4 and 3.5 discuss our empirical results on interconnectedness in loan syndications and the implications of such interconnectedness for systemic risk. Finally, we conclude in Section 3.6 with some policy implications.

3.2 Empirical Methodolgy

In this section, we first develop our interconnectedness measure and then briefly describe the different systemic risk measures used in our empirical tests. All variables are defined in Table 3.1.

3.2.1 Measuring Interconnectedness

In this subsection, we describe how we measure distance between two banks based on lending specializations. We then explain how we construct our interconnectedness measure.

3.2.1.1 Distance between Two Banks

We analyze bank syndicated loan specialization related to U.S. borrower industry and borrower geographic locations. Specifically, we use the 2-digit borrower's SIC industry code and the borrower's U.S. state in which it has its headquarter to examine in which area(s) each bank has heavily invested.[11] Analyzing specializations along industries and regions captures two key diversification dimensions of banks' risk management.[12] We then compute the distance between two banks by quantifying the similarity of their loan portfolios. The detailed construction of our distance measure is as follows.

[10] While new syndicated loan origination declined during the 2007-2008 financial crisis in the US, the total lending exposure on banks' balance sheet increased substantially (Ivashina and Scharfstein (2010)). Borrowers started to draw down credit lines that have been committed by banks during the period of credit expansion. In fact, a large percentage of loans in the Dealscan sample are credit lines (Berg et al. (2016)). In other words, the committed amounts of loans that have been originated before the recession period are a good proxy for the portfolio of banks when they enter the recession. We do not differentiate between credit lines and term loans when calculating our interconnectedness measure and our proxies thus captures the drawn credit line exposures.

[11] We also examine lender specialization at different aggregation levels for borrower industry (SIC industry division, 3-digit SIC industries, 4-digit SIC industries) and borrower geographic location (U.S. region, 3-digit zip code). We obtain very similar results.

[12] Note that U.S. borrower geographic location and industry are correlated. Certain industries tend to concentrate in certain areas. For example, WY, WV, LA, OK, and TX have higher concentration in mining, whereas WI, VT, OH, IN, OR, NC, and CT are more specialized in manufacturing. Consequently, we expect borrower geographic location to generate results somewhat similar to those based on borrower industry.

For each month during the January 1989 to June 2011 period, we compute each lead arranger's total loan facility amount it originated during the prior 12 months, using Dealscan's loan origination data.[13] There were approximately 70-125 active lead arrangers each month in the U.S. syndicated loan market; as a result, we obtain 27,117 unique lead arranger-months. We then compute portfolio weights for each lead arranger in each specialization category (2-digit borrower SIC industry, borrower headquarter U.S. state). Let $w_{i,j,t}$ be the weight lead arranger i invests in specialization (e.g. industry) j within 12 months prior to month t. Note that for all pairs of i and t, $\sum_{j=1}^{J} w_{i,j,t} = 1$, where J is the number of industries, or geographic locations the lender can be specialized in.

Next, we compute the distance between two banks as the Euclidean distance between them in this J-dimension space:

$$Distance_{i,k,t} = \frac{1}{\sqrt{2}} \times \sqrt{\sum_{j=1}^{J} (w_{i,j,t} - w_{k,j,t})^2}, \tag{3.1}$$

where $Distance_{i,k,t}$ is the distance between bank i and bank k in month t ($i \neq k$). The distance measure is normalized to a scale of 0-1 with 0 reflecting no distance (complete portfolio matching) and 1 reflecting full distance (i.e. no portfolio overlap). Appendix A.3.2 provides an example on how distance between two banks is computed as specified in (3.1). For illustrative purposes, we discuss the computation of our distance measures based on borrower SIC industry for JPMorgan Chase, Bank of America, and Citigroup. These three banks were the top three lead arrangers as of January 2007 according to their portfolios of syndicated loans originated during the prior twelve months (i.e. January-December 2006). Citigroup had a different loan portfolio from those held by either JPMorgan Chase or Bank of America, investing more heavily in the manufacturing, transportation, communications, electric, gas, sanitary, and services industries and less heavily in retail trade, finance, insurance and real estate. As a result, the distance computed between Citigroup and either JPMorgan Chase or Bank of America is greater than the distance between JPMorgan Chase and Bank of America whose portfolios were more similar to each other. We show the pairwise distance in Appendix A.3.3.

3.2.1.2 Bank-level Interconnectedness

To measure monthly interconnectedness at the bank-level, we first take the weighted average of the distance between a given lead arranger and all the other lead arrangers in the syndicated loan market. As a smaller Euclidean distance means higher interconnectedness, we then linearly transform the weighted average of distance into an interconnectedness measure for the lead arranger. Our measure is normalized to a scale of 0-100 with 0 being least interconnected and 100 being most interconnected.[14] That is, a higher value indi-

[13] The loan amount is split equally over all lead arrangers for loans with multiple leads.

[14] We can also interpret an interconnectedness value of 0 as being not interconnected at all (i.e., having a loan portfolio completely different from all the other lead arrangers' portfolios) and 100 as being totally interconnected (i.e., have a loan portfolio exactly same as all the other lead arrangers' portfolios).

cates a more interconnected bank. Specifically, the interconnectedness of bank i in month t, $Interconnectedness_{i,t}$, equals:

$$Interconnectedness_{i,t} = \left(1 - \sum_{k \neq i} x_{i,k,t} \cdot Distance_{i,k,t}\right) \times 100, \tag{3.2}$$

where $Distance_{i,k,t}$ is the distance between bank i and bank k in month t as defined in (3.1), and $x_{i,k,t}$ is the weight given to bank k in the computation of bank i's interconnectedness. We use three kinds of weighting schemes for $x_{i,k,t}$ We assign equal weights to all other banks ("equal-weighted interconnectedness"). This is our baseline specification to separate the (incremental) effect of adjusting weights to capture two distinct bank characteristics (size, and lending relationships). Specifically, we construct also a size weight of loan holdings where larger banks may matter more for systemic risk ("size-weighted interconnectedness"). The weights are computed based on the lagged total assets of bank k relative to the sum of lagged total assets of all other banks in the syndicated loan market. Finally, we construct a relationship-weighted measure of interconnectedness to capture the importance of lending relationships among lead arrangers for the overlap of bank's syndicated loan portfolios ("relationship-weighted interconnectedness"). The idea here is to capture implicit relationships in sharing loan syndication among closely related (compared to distantly related) banks.[15] Specifically, the weight is calculated based on the number of collaborative relationships between bank i and bank k relative to the total number of relationships bank i had with all banks in the syndicated loan market during the prior twelve months.[16] Appendix A.3.4 provides an illustrative example on how all three different weights among banks are computed.

3.2.1.3 Market-aggregate Interconnectedness

We use our individual bank measures to construct monthly Interconnectedness Indexes aggregating bank-level interconnectedness to the market level using a simple average. As we have three weighting schemes on the bank level (equal-, size-, and relationship-weighting), we obtain three monthly Interconnectedness Indexes.

$$Interconnectedness\, Index_t = \sum_i \frac{1}{N_t} \times Interconnectedness_{i,t}, \tag{3.3}$$

where $Interconnectedness_{i,t}$ is the interconnectedness of bank i in month t as defined in (3.2) and N_t is the number of connected banks as of month t.[17]

[15] We also constructed a fourth weighting scheme using the actual U.S. dollar exposures of banks to the same borrowers ("exposure-weighted interconnectedness"). Our main results of the paper do not change under this fourth weighting scheme.

[16] A collaborative relationship is identified if bank k is bank i's participant lender, co-lead, or lead arranger.

[17] Instead of using a simple average, we could also use e.g. bank size to aggregate the bank-level interconnectedness to the market level. The results do not change and are not reported for brevity.

3.2.2 Measuring Systemic Risk

To analyze the link between loan portfolio interconnectedness and systemic risk, we use three bank-level systemic risk measures proposed in the recent literature: (i) SRISK, (ii) DIP, and (iii) CoVaR. These measures are briefly described below.

3.2.2.1 SRISK

SRISK is a bank's U.S.-Dollar capital shortfall if a systemic crisis occurs, which is defined as a 40% decline in aggregate banking system equity over a 6-month period. This measure is developed in Acharya et al. (2017) and Brownlees and Engle (2017). SRISK is defined as

$$\begin{aligned} SRISK &= E((k(D + MV) - MV) \mid Crisis) \\ &= kD - (1 - k)(1 - LRMES)MV, \end{aligned} \tag{3.4}$$

where D is the book value of debt which is assumed to be unchanged over the crisis period, LRMES is long-run marginal expected shortfall that measures the co-movement of a bank's stock price with the stock market index when the overall market return falls by 40% over the crisis period.[18] $LRMES \times MV$ is then the expected loss in market value of a bank over this 6-month window. k is the prudential capital ratio which is assumed to be 8% for U.S. banks and 5.5% for European banks to account for differences between US-GAAP and IFRS measures. SRISK thus combines both the firm's projected market value loss due to its sensitivity to market movements and its leverage. Naturally, SRISK is larger for larger banks. To make sure our results are not driven solely by bank size, we conduct various tests and carefully control for bank size in our tests.

3.2.2.2 DIP

We use the DIP as our second market-based measure of systemic risk (Huang et al. (2009) Huang et al. (2012); Black et al. (2013)). The four main components of DIP are: (1) the risk-neutral probability of default (PD), which is calculated from CDS prices using (2) loss given default (LGD) estimates, which can vary over time, (3) asset correlations which are measured using equity return correlations, and (4) the total liabilities of all banks.

Huang et al. (2009) construct a hypothetical portfolio of the total liabilities of all banks and use Monte-Carlo simulations to estimate the risk neutral probability distribution of credit losses for that portfolio. DIP is then a hypothetical insurance premium to cover losses if total losses (L) (aggregated over all banks) exceeds a certain threshold of a banks' total liabilities (L_{min}). DIP can then be expressed as follows:

$$\begin{aligned} DIP &= E^Q(L \mid L > L_{min}) \\ \frac{\partial DIP}{\partial L^i} &= E^Q(L^i \mid L > L_{min}) \end{aligned} \tag{3.5}$$

[18] V-Lab uses the S&P 500 for U.S. banks and the MSCI ACWI World ETF Index for European banks.

DIP describes a conditional expectation of portfolio losses under extreme conditions. It is thus similar to an expected shortfall concept, but is not defined using a percentile distribution but rather by using an absolute loss threshold (L_{min}). In that sense, it is also similar to SRISK.[19] L^i is then the loss of an individual institution and determines the marginal contribution of a bank to the systemic risk of the financial sector ($\frac{\partial DIP}{\partial L^i}$). While we consistently refer to this measure as "DIP" throughout the paper, we operationalize it using the loss of each individual bank in the regressions (i.e., L^i).

3.2.2.3 CoVaR

Our third market-based measure of systemic risk is CoVaR (Adrian and Brunnermeier (2016)). CoVaR is the value at risk (VaR) of the financial system conditional on one institution being in distress and $\Delta CoVaR$ is the marginal contribution of that firm to systemic risk. The VaR of each institution is measured using quantile regressions and the authors use a 1% and 5% quantile to measure CoVaR:

$$Prob(L \geq CoVaR_q \mid L^i \geq VaR_q^i) = q, \tag{3.6}$$

where L is the loss of the financial system, L^i is the loss of institution i, and q is the VaR quantile (for example, 1%). Thus, CoVaR measures spillovers from one institution to the whole financial system. Importantly, CoVaR does not imply causality, i.e., it does not imply that a firm in distress causes the systemic stress of the system, but rather suggests that it could be both, a causal link and/or a common factor (in terms of asset or funding commonality) that drives a bank's systemic risk contribution.

CoVaR is not as sensitive to size or leverage as SRISK. Moreover, in contrast to SRISK, CoVaR includes only the correlation with market return volatility, but not a bank's return volatility. Suppose that two banks have the same market return correlation, but bank A has low volatility while bank B has high volatility. Both banks would have the same CoVaR even though bank A is essentially of low risk.

3.2.2.4 Comparing the three bank-level systemic risk measures

We use the three different systemic risk measures above, as they capture different aspects of systemic risk. SRISK captures the consequences for an *individual* bank resulting from a 40% equity decline of the entire *aggregated* banking system. DIP (similar to SRISK) captures the loss of an *individual* bank conditional on expectations of the *aggregated* banking sector being under extreme conditions. CoVaR analyzes the reverse. It captures the VaR of the *aggregated* financial system resulting from an *individual* institution being in

[19] The major methodological difference between DIP, SRISK and CoVaR is that DIP is a risk-neutral measure, while SRISK and CoVaR are statistical measures using physical distributions. From an economic perspective, DIP is different compared to shortfall measures such as SRISK as the CDS spreads used to calculate default risk measure the potential losses to debt holders assuming all equity is wiped out. One can therefore also refer to DIP as a "bailout measure," which is quite often the focus in policy discussions of this measure.

distress.

These differences might also affect the sensitivities of the systemic risk measures to interconnectedness during both expansions and recessions. Interconnectedness might have a larger impact on SRISK and DIP during recessions. During recessions, banks' capital levels and therefore loss absorbing capacities are lower. This is exactly when banks are most vulnerable, so that higher interconnectedness may facilitate spillovers when the system as a whole is shocked.

The sensitivity of the CoVaR measure is less obvious. In expansions, a large shock of a single institution may lead to less severe spillovers to the whole financial system, but might have a large impact to the sensitivity of VaR tail-risks as vulnerabilities of all other banks rise. In recessions, spillovers should be larger, but given that the whole financial system was just shocked by a common factor, the marginal impact on changes to the VaR tail-risks might be lower. The effect of interconnectedness on CoVaR might thus be lower relative to the other two systemic risk measures.

3.3 Data and Summary Statistics

In this section, we discuss our data sources and provide summary statistics.

3.3.1 Data Sources

We use two primary sources of data to analyze the interconnectedness of banks in loan syndication and how such interconnectedness affects banks' systemic risk: (i) syndicated loan data and (ii) systemic risk data. Thomson Reuters LPC DealScan is the primary database on syndicated loans with comprehensive coverage, especially for the U.S. market. We use a sample of 90,578 syndicated loan facilities originated for U.S. firms between January 1988 and June 2011 to construct our distance and interconnectedness measures.[20] These loans present very similar characteristics as documented in the literature, e.g., Sufi (2007) and Ivashina (2009). We also follow that literature identifying the lead arranger of the syndicate.

We measure interconnectedness at the lead arranger (bank holding company) level for different reasons. Lead arrangers establish the relationship with the borrowing firm and decide on the syndication structure of the loan. In addition, lead arrangers take larger shares in the syndicated loan due to information asymmetries between the lead arranger and participants (Sufi (2007)).[21]

[20] We have an original sample of 91,715 syndicated loan facilities. However, we restrict ourselves to lead arrangers that originated at least ten syndicated loans in the sample period to exclude lead arranger that only randomly enter the syndicated loan market (these are usually very small banks that should matter less for the interconnectedness of a bank and the banks' systemic risk). In total, our sample consists of 223 lead arrangers. We receive very similar results, if we do not restrict the number of lead arrangers.

[21] Lead arrangers (usually one or two per syndicated loan) each hold, on average, a 30 percent share in the syndicated loan, while participants hold, an average, 8 percent each. Dealscan has limited information about the loan shares retained by banks at origination. The subsample with loan share information comprises about 20 percent of the loan observations.

We use lead banks, as they also actively participate. Lender arrangements in about seven out of ten syndicated loans are reciprocal in the sense that lead arrangers also participate in loans that are led by their participant lenders (Cai (2010)). Thus, lead arrangers are a source of interconnectedness as they syndicate loans for others to be exposed to their loan portfolio risk, and at the same time, they are exposed to other banks' loan portfolio risk as they participate. This is not the case for banks that are only participants (but never lead arrangers). These participant banks are passively chosen by lead arrangers in loan syndicates but do not actively increase interconnectedness with other large lenders in the syndicated loan market.

Importantly, we show in this paper that lead arrangers work together with banks that have similar portfolios measured by loan portfolio allocation as lead arrangers as well as those they have previous relationship based on loan market collaboration. In other words, their allocation as lead arrangers should be close to the portfolio allocation as participants.

Our sample of lead arrangers consists of U.S. institutions as well as large international institutions that have significant syndicated loan exposure originated in the U.S. market.[22] Moreover, 26 of 28 Globally Significant Financial Institutions (G-SIFIs) are included in our sample.

Using lead bank data can thus be a good approximation for loan participation, in particular for loan participation arising from (systemically relevant) reciprocal relationships as lead and participants. As alluded to above, these comprise the major part of syndicated loan participants.

We obtain the SRISK data from NYU V-Lab's Systemic Risk database and the DIP and CoVaR data from the authors who proposed them as systemic risk measures. SRISK data covers 132 global financial institutions and 16,258 bank-months ranging from January 2000 to December 2011. We are able to match them with 5,733 lead arranger-months and 58 unique lead arrangers. The DIP data are weekly covering 57 unique European financial institutions from January 2002 to January 2013. We aggregate weekly data into monthly measures and obtain 5,235 bank-months with DIP measures. We are able to construct a matched sample of 19 unique lead arrangers and 1,343 lead arranger-months with our interconnectedness data. The CoVaR data are quarterly covering 1,194 public U.S. financial institutions and 62,642 bank-quarters ranging from the first quarter of 1986 to the fourth quarter of 2010. We are able to match them with 1,716 lead arranger-quarters and 38 unique lead arrangers.[23] In our regressions, we use CoVaR data starting in the first quarter of 2000 to ensure comparability across our three systemic risk measures when computing the portfolio overlap.

[22] Non-U.S. financial institutions have large exposures to U.S. borrowers. For example, we document in Appendix A.3.3, that five European banks are among the top ten lead arrangers in the U.S. syndicated loan market as of January 2007. Overall, non-U.S. lead arrangers originated 17.4% of the total loan amount in the U.S. syndicated loan market.

[23] The appendix contains a lists lead arrangers for which the various systemic risk measures are available.

3.3.2 Summary Statistics

Table 3.2 reports summary statistics for the distance, interconnectedness, and systemic risk measures described in Section 3.2 as well as lead arranger (bank) and market characteristics. Distance is summarized for approximately 2,700,000 lead arranger pair-months and interconnectedness of roughly 26,500 lead arranger-months across the two lender specialization categories and three interconnectedness weightings. Lender specialization can be by industry and geographic location, while interconnectedness can be equal-, size-, and relationship-weighted. By definition, distance must lie within the range of 0 to 1 and interconnectedness within the range of 0 to 100. The standard deviations of these measures imply that there is sufficient variation for empirical tests. Further, the distribution of our distance measures indicate a similar variation of lender specialization differences across banks for both industry and geographic location. This similarity of variations in industry and geographic location specializations carries over to the bank-level and market aggregate interconnectedness measures. However, our different weighting schemes do capture distinct differences in the interconnectedness of lead arrangers. The size-, and relationship-weighted interconnectedness measures are on average much larger than the baseline equally-weighted measure. Furthermore, lending relationships appear to matter more for interconnectedness than size. This result holds for both the bank-level and the market-aggregate interconnectedness measures.

Summary statistics of SRISK, DIP, and CoVaR are reported at the lead arranger level. Our SRISK data consists of 5,733 matched lead arranger-months from U.S. and international institutions heavily invested in the U.S. syndicated loan market, and the average SRISK is $25.3 billion. Our DIP data consists of 1,343 matched lead arranger-months from European banks heavily invested in the U.S. syndicated loan market, and the average DIP is $20.4 billion converted into U.S. dollar-values based on the exchange rate at beginning of year 2009. Our CoVaR data consists of 1,716 matched lead arranger-quarters from U.S. institutions, with the 1% CoVaR equal to a decline of $15.8 billion in bank equity value on average.[24] All these measures show greater systemic risk for our sample of lead arrangers than an "average" financial institution in the SRISK, DIP, and CoVaR data sets.[25] The SRISK measure and DIP measure have correlations close to 0.8 for the sample of lead arrangers for which the data is available. The correlation between SRISK and CoVaR is about 0.2.[26]

[24]The CoVaR data are all expressed in the form of losses, i.e., negative numbers. In our empirical analyses, we multiply CoVaR with minus one so that a higher CoVaR implies higher systemic risk.

[25]For example, the SRISK of an average financial institution is $10.3 billion. An average public U.S. financial institution in the 1% CoVaR data shows a decline of $0.785 billion, and an average European financial institution in the DIP data shows a DIP of $10.9 billion.

[26]In our sample, the DIP and CoVaR measures do not overlap, as our CoVaR sample comprises U.S. institutions, while our DIP sample includes European banks.

3.4 Interconnectedness of Banks in Loan Markets

In this section, we first empirically examine how banks become interconnectedness in the U.S. syndicated loan market. We then explore the determinants of interconnectedness and analyze the trend of interconnectedness over time.

3.4.1 How Do Banks Become Interconnected?

To understand commonality of banks' syndicated corporate loan portfolio, we first examine how banks become interconnected in the syndicated loan market. In order to make our data and computations manageable, we limit our interest to the top 100 lead arrangers in each month that hold an aggregated share of at least 99.5% of the total market. We estimate the following regression:

$$\begin{aligned} Syndicate\,Member_{i,k,n,t} = \alpha &+ \beta_1 \cdot Distance_{i,k,t} + \beta_2 \cdot Lead\,Relationship_{i,k,t} \\ &+ \beta_3 \cdot Borrower\,Relationship_{k,n} + \beta_4 \cdot Market\,Share_{k,t} \\ &+ Loan\,Facility_n^{'} + e_{i,k,n,t} \end{aligned} \tag{3.7}$$

where the dependent variable $Syndicate\,Member_{i,k,n,t}$ is an indicator variable that equals one if lead arranger i chooses lender k as a member in loan syndicate n that is originated in month t and zero otherwise. $Distance_{i,k,t}$ measures the distance between lead arranger i and lender k based on their syndicated loan portfolios during the twelve months prior to month t. As a proxy for bank-to-bank relationships, $Lead\,Relationship_{i,k,t}$ is an indicator variable for whether lead arranger i had syndicated any loans with lender k prior to the current loan (no matter what roles the two lenders took). As a measure of bank-firm relationships, $Borrower\,Relationship_{k,n}$ is an indicator variable for whether lender k arranged or participated in any syndicated loans that were made to the borrower prior to loan syndicate n. By including $Lead\,Relationship_{i,k,t}$ and $Borrower\,Relationship_{k,n}$ in the regression, we control for the effects of prior relationships between the two lenders and prior relationships between the borrower and lender k on the construction of the syndicate. $Market\,Share_{k,t}$ is the market share of lender k as a lead arranger during the twelve months prior to month t. We use $Market\,Share_{k,t}$ to proxy for lender k's reputation and market size or power. $Loan\,Facility_n$ is a vector of loan facility fixed effects, which are included to rule out any facility-specific effects. Standard errors are heteroscedasticity robust and clustered at the lead arranger level. The resulting sample size is almost 11 million lender pairs.

The results are reported in Table 3.3. In all regressions, our distance measures show negative coefficients that are significant at the 1% level. That is, the greater the portfolio similarity between a lender and the lead arranger, the greater the likelihood that the lender is chosen as a syndicate member. We also find that a lender's prior relationships with either the lead arranger or the borrower have significantly positive influence on the likelihood of being chosen as a syndicate member. The effect is especially strong for prior lender-borrower relationships, which is consistent with the findings in Sufi (2007). Moreover, lender k's market share increases its likelihood of being included in the syndicate.

Overall, the results suggest that lead arrangers tend to work with banks that have more similar corporate loan portfolios increasing the degree of bank interconnectedness over time.

3.4.2 Determinants of Interconnectedness

To understand the determinants of interconnectedness, we examine the effect of three bank characteristics, (i) total assets, (ii) diversification, and (ii) number of specializations and loan market size. Total assets is a standard proxy for bank size; the other two variables indicate the level of diversification and breadth of the bank's syndicated loan portfolio. While the variables diversification and number of specializations are related, there is a subtle difference: diversification considers the individual syndicated loan amounts to determine each specialization's portfolio weight, whereas the number of specializations only counts specializations independent from the loan amount.[27]

We first examine correlation between interconnectedness and each of the three variables. Then, we estimate the following multiple regression model:

$$\begin{aligned} Interconnectedness_{i,t} = \alpha + &\beta_1 \cdot Total\,Assets_{i,t} + \beta_2 \cdot Market\,Size_t \\ &+ \beta_3 \cdot Diversification_{i,t} + \beta_4 \cdot Number\,of\,Specializations_{i,t} \\ &+ Lead\,Arranger_i + e_{i,t} \end{aligned} \tag{3.8}$$

where the dependent variable $Interconnectedness_{i,t}$ is the level of interconnectedness of bank i in month t. $Total\,Assets_{i,t}$ is bank i's lagged total assets at the beginning of month t; $Market\,Size_t$ is the total issuance volume in the 12 months prior to loan origination capturing a possible effect of syndicated loan market size on bank interconnectedness. For example, more lending associated with a larger syndicated loan market might mechanically increase interconnectedness because banks are no longer are available to avoid each other in their lending specialization. $Diversification_{i,t}$ is the diversification measure computed as in equation (3.9) below:

$$Diversification_{i,t} = \left[1 - \sum_{j=1}^{J} (w_{i,j,t})^2\right] \times 100, \tag{3.9}$$

where $Diversification_{i,t}$ measures the diversification level of bank i in month t and, as in (3.1), $w_{i,j,t}$ is the weight bank i invests in specialization j (e.g. industry) within 12 months prior to month t.[28] $Number\,of\,Specializations_{i,t}$ is the number of specializations the bank is engaged in as a lead arranger.[29] $Lead\,Arranger_i$ is a vector of lead arranger (bank)

[27] The Pearson correlation between both measures is about 0.7.

[28] The notion behind the measure is that as a bank becomes more diversified, $\sum_{j=1}^{J}(w_{i,j,t})^2$ becomes smaller, so that the measure for diversification grows larger.

[29] Number of Specializationi,t varies by the type of specializations. For the specialization by borrower

fixed effects. Fahlenbrach et al. (2012) report that bank business models and risk culture are persistent and they might affect a bank's decision to become more interconnected. Standard errors are heteroscedasticity robust and clustered at the lead arranger level.

Table 3.4 reports the results for both specializations by borrower industry and borrower geographic location using our three types of weightings. First, we show in Panel A significantly positive Pearson correlation coefficients between interconnectedness and total assets, market size in the syndicated loan market, diversification, and number of specializations, all at the 1% level, indicating a positive association of these variables with interconnectedness. The square of the Pearson correlation coefficient helps to assess the explanatory power of these four variables for interconnectedness. We find that the size variables, total assets and market size, have Pearson correlations ranging from 0.30 to 0.40 and 0.21 to 0.30, respectively. This corresponds to an explanatory power of these variables for interconnectedness in an univariate setting of 9% to 16% and 4% to 10%, respectively. In contrast, diversification and number of specializations have a Pearson correlation in the range of 0.93 to 0.98 and 0.73 to 0.76, respectively. This corresponds to an explanatory power of these variables for interconnectedness in an univariate setting of 86% to 96% and 53% to 58%, respectively. In other words, banks with concentrated loan portfolios are less interconnected relative to those with diversified portfolios. Overall, diversification and number of specialization are relatively more important determinants of loan market interconnectedness than bank size and market size.

We include next all variables in multivariate regressions and report the results in Table 3.4 Panel B. We continue to find positive effects of total assets, market size, diversification, and number of specializations on interconnectedness.[30] While the coefficients on diversification, number of specializations and market size are all significant at the 1% level, the coefficients on total assets are sometimes less or not significant in the aggregations by industry specialization. Consistent with the correlation results, diversification is a main driver of interconnectedness in all regressions.

3.4.3 Time Trends in Interconnectedness

We next investigate time-series properties of our interconnectedness measures across our three weighting schemes (i.e. equal-, size-, and relationship-weighted) over the January 1989 to June 2011 period in Figures 3.1 to 3.3.[31]

At the market-aggregate level, size-, and relationship-weighted interconnectedness are consistently greater than the baseline equal-weighted counterpart throughout our sample, whereas relationship-weighted interconnectedness is consistently the largest (see Figure

industry, it is the number of 2-digit borrower SIC industries. For the specialization by borrower geographic location, it is the number of U.S. states.

[30] The results are robust to regressions specifications without the Lead Fixed Effects, in which we include dummy variables for commercial bank, and dummies for headquarter locations for Europe, as well as outside U.S. and Europe to control for heterogeneity across lead arrangers.

[31] All figures are based on industry aggregation. Figures for regional aggregation are very similar but remain unreported for brevity.

3.1). Higher relationship-weighted interconnectedness indicates that banks tend to establish lending relationships with those banks that have similar asset allocations in their syndicated loan portfolios. Higher size-weighted interconnectedness compared to equal-weighted interconnectedness indicates that bank's asset allocations is on average more similar to larger banks compared to smaller banks. In addition, we observe a sharp increase in the difference between the size-weighted interconnectedness and the equal-weighted interconnectedness from the early 1990s until 2007 and again after the financial crisis of 2008 and 2009 consistent with the interpretation that banks become too large and too interconnected to fail during the financial crisis (Acharya and Yorulmazer (2008)).[32] During the last two recession periods, in 2001 and 2008-2009, interconnectedness dropped significantly, but rose again following both periods.[33]

At the bank-level, we observe that banks who are frequently lead arrangers in the loan syndicated market (e.g. Bank of America) have consistently higher, and tend to have less volatile, interconnectedness measures than banks who play a smaller role in this market (e.g. Morgan Stanley), see Figure 3.2. Given their importance as lead arranger, large lenders in the syndicated loan market, such as Bank of America, may not be able to specialize in certain industries or regions but originate loans across all regions and industries. In contrast, Morgan Stanley, as a medium-size lead arranger in the syndicated loan market, has more flexibility to structure its portfolio. This is demonstrated for example by the sharp drops in Morgan Stanley's interconnectedness following the last two recession periods comparted to Bank of America.[34]

Importantly, the plots generally show a fair amount of stability from year to year with our interconnectedness measure, particularly in periods of expansion.[35] This is important as the interconnectedness measure should be used by policy makers to assess the build-up of systemic risk during normal times. Wide time-series variation in interconnectedness during expansions would make the optimal policy more difficult to implement.

Figure 3.3 plots the equal-weighted and size-weighted interconnectedness measure for Bank of America (Panel A) and Morgan Stanley (Panel B) as well the difference between both time-series. Consistent with Figure 3.1, the plots show that size-weighted interconnectedness measure is larger compared with the equal-weighted measure and this difference

[32] Consistent with this interpretation, cross-sectional analyses show that the fraction of banks with the highest interconnectedness also increased prior to the financial crisis of 2008 to 2009.

[33] Minoiu and Reyes (2013) find the same cyclicality when studying the interconnectedness of entire banking systems across countries.

[34] For example, Morgan Stanley reduced the lending in the syndicated loan market during the recent crisis and adjusted the asset allocation. It focused lending almost entirely to two industries, namely chemical and allied products as well as electronic and other electronic equipment and components – out of mining, construction, electric, gas and sanitary services, and engineering, accounting, research and management services. Its geographical specializations primarily focused on Michigan, and also to California and New Jersey – and out of New York and Texas.

[35] We also analyze the time-series correlation of the bank-level interconnectedness measures which supports the stability of our measure. For example, the time-series correlation among the top three U.S. lead arrangers (JPMorgan Chase, Bank of America, and Citigroup) averages 0.84, and the time-series correlation among Credit Suisse and UBS is 0.82. In addition, the time-series correlations among U.S. banks and among European banks tend to be higher than between U.S. banks and European banks.

is even increasing, particularly for important originators such as Bank of America. I.e. banks that play a larger or smaller role in the market tend to increase their syndicate portfolio overlap particularly with large banks consistent with the moral hazard theories mentioned above.

3.5 Interconnectedness and Systemic Risk

In this section, we investigate whether our bank-level interconnectedness measures increase bank's systemic risk (SRISK, DIP, and CoVaR) during recessions.

3.5.1 Bank-level Tests - Methodology

Interconnectedness in the syndicated loan market creates the potential for enhanced systemic risk. Banks become more vulnerable to common shocks as exposure to similar assets and banks can spread throughout the syndicate network to other banks.

To examine this, we match the bank-level systemic risk measures SRISK, CoVaR, and DIP with the time-series of our bank-level interconnectedness measure. To test their relationship, we first univariately examine the correlation between systemic risk and interconnectedness. Table 3.5 shows that Pearson correlation coefficients between interconnectedness and all three bank-level systemic risk measures (SRISK, DIP, and CoVaR) are significantly positive at the 1% level.

In a second step, we add control variables in a multiple regression setting. The general form of the regression we estimate is as follows:

$$\begin{aligned} Systemic\,Risk_{i,t} &= \alpha + \beta_1 \cdot (Interconnectedness_{i,t} \times Expansion_t) \\ &+ \beta_2 \cdot (Interconnectedness_{i,t} \times Recession_t) + \beta_3 \cdot Recession_t \\ &+ \beta_4 \cdot Total\,Assets_{i,t} + \beta_5 \cdot Market\,Share_{i,t} + \beta_6 \cdot Market\,Size_t \\ &+ \beta_7 \cdot Systemic\,Risk_{i,t-1} + Lead\,Arranger_i' + e_{i,t} \end{aligned} \tag{3.10}$$

The dependent variable $Systemic\,Risk_{i,t}$ is the systemic risk measure of bank i in month t, which can be either SRISK, DIP or CoVaR. The key independent variable $Interconnectedness_{i,t}$ is the level of interconnectedness of bank i in month t. To distinguish between the effect of interconnectedness on systemic risk during periods of expansions and recessions, we include two interaction terms in the regression: $(Interconnectedness_{i,t} \times Expansion_t)$ and $(Interconnectedness_{i,t} \times Recession_t)$.
$Recession_t$ $(Expansion_t)$ is an indicator variable equal to one if month t falls into recessions (expansion) as measured by NBER recession dates.[36] We control for bank size $(Total\,Assets_{i,t})$, market power in loan syndication $(Market\,Share_{i,t})$ and market size of the U.S. syndicated loan market $(Market\,Size_t)$. A one-period lagged systemic risk mea-

[36] The NBER identifies three recession periods during our sample period: July 1990 – March 1991, March 2001 – November 2001, and December 2007 – June 2009.

sure ($Systemic\,Risk_{i,t-1}$) is included on the right hand side of the regression to account for serial correlation. We further include lead arranger (bank) fixed effects. Standard errors are heteroscedasticity robust and clustered at the lead arranger level. To analyze whether interconnectedness has a stronger effect on systemic risk during recessions compared to expansions, we formally test the following hypothesis,

$$H0 : \beta_2 - \beta_1 = 0 \tag{3.11}$$

3.5.2 Interconnectedness and SRISK

Table 3.6 reports the regression results for SRISK based on 57 unique lead arrangers[37] with monthly data ranging from January 2000 to June 2011. In all specifications, we find statistically and economically insignificant coefficients on the interaction term interconnectedness and expansion. That is, during periods of economic expansions, interconnectedness neither elevates nor reduces SRISK. However, our empirical findings show that all coefficients on the interaction term between interconnectedness and NBER recessions are consistently positive and statistically significant at the 1% level. The effect is also economically significant: i.e. an increase of one standard deviation in interconnectedness during recessions leads to a total SRISK increase of \$4.4 to \$8.9 billion when the past six to twelve month were in recession, which is approximately a 17% to 35% increase from the mean SRISK. Formally testing the difference in the interaction terms between interconnectedness and recession with interconnectedness and recession consistently shows statistical significance at the 1% level.[38] These results show that interconnectedness contributes more positively to SRISK during recessions consistent with an amplifying effect of interconnectedness on systemic risk during recessions as suggested by Bernanke (2010). Our finding is also consistent with our prior as to the effect of interconnectedness on SRISK when banks are vulnerable to recessions (see section 3.2.2.4).

The coefficients on a bank's total assets are significantly positive indicating that larger banks are more sensitive to systemic risk.[39] The effect of market share as a lead arranger in the syndicated loan market on SRISK is insignificant. The coefficient on market size is marginally positive and significant. The one-month lagged SRISK has significantly positive

[37] Note that the number of lead arrangers slightly reduces from our matched SRISK and interconnectedness dataset described above, as the regression specification requires the total assets variable and a lagged SRISK measure. The same applies to the CoVaR and DIP regressions.

[38] The results are robust to restricting the sample to positive SRISK, that is, when financial institutions have a capital shortfall.

[39] These results are consistent with our earlier results describing the drivers of interconnectedness in corporate loan markets. While bank size is an important factor, it is not a sufficient condition that eventually explains cross-sectional variation in interconnectedness and eventually systemic risk. Recent events provide a supporting narrative. For example, the default of the Portuguese lender Banco Espirito Santo (a relatively small bank with assets worth EUR 81 billion) caused a global stock market decline in July 2014. Similarly, the Swiss regulator declared the Raiffeisenbank Schweiz Genossenschaft, a bank with assets of EUR 28 billion, "systemically important" in August 2014 because its products cannot be easily replaced and are important for the Swiss economy. In other words, systemic importance of banks extends beyond size, and it is crucial to monitor other factors such as interconnectedness of banks.

coefficients consistently around 0.9 showing high persistence of SRISK over time.[40]

3.5.3 Interconnectedness and DIP

Table 3.7 reports OLS regression results for our systemic risk measure DIP using 19 unique lead arrangers (European banks) with monthly data ranging from February 2002 to June 2011 using the same regressions specification (3.10) as above.

Similar to results for SRISK, we find that the coefficient of the interaction term of interconnectedness and expansion is not statistically and economically significant. Further, all coefficients of the interaction term of interconnectedness with NBER recessions are significantly positive at the 1% level. Testing our H0-hypothesis shows that these two interaction coefficients are significantly different at the 1% level, that is higher interconnectedness increases DIP during recessions, but not during normal times. This effect is also an economically significant as an increase of one standard deviation in interconnectedness during recessions is related to an increase of \$7.3 to \$11.1 billion in DIP when the last six to twelve month were in recession, which represents a 36% to 54% increase from the average DIP.

Table 3.7 also shows that a great amount of variation in DIP is explained by a bank size. The effect of market size is statistically significant, but economically small. Consistent with our SRISK results, market share is usually not statistically significant and DIP displays high persistence (around 0.75) over time.

3.5.4 Interconnectedness and CoVaR

Table 3.8 reports the multiple regression results for 1% CoVaR based on 36 unique U.S. lead arrangers with quarterly data ranging from the first quarter of 2000 until the fourth quarter of 2010. The regressions have the same specifications as above.

Results consistently show small and insignificant coefficients on the interaction term of interconnectedness and expansion for all specifications. The coefficients on the interaction term of interconnectedness and recession are consistently positive and statistically significant at the 5% or 10% level.[41] Overall, these findings show a magnifying effect of interconnectedness on CoVaR during recessions.[42] The results are also highly significant in economic terms: an increase of interconnectedness by one standard deviation during recessions results in a total increase of \$3.3-4.8 billion in 1% CoVaR when the last six month were recession periods. Such increases are elevations of about 21%-30% from the average 1% CoVaR measures. The effect of interconnectedness on CoVaR during recessions is smaller as compared to, e.g. SRISK or DIP. As described above, a possible interpretation is that the marginal impact of an increase in individual bank risk on the market is smaller

[40] We also run tests using LRMES, which is a main component of SRISK and more of a measure of tail risk, as the dependent variable. Our main results and conclusions do not change.

[41] While the difference between both interaction coefficients are large in magnitude, they are not statistically significant (but almost at the 10% level) as our tests of the H0-hypothesis show.

[42] The results are robust to analyzing the 5% CoVaR instead of the 1% CoVaR.

when the economy is already in a recession.

As mentioned in Section 3.2.2, CoVaR is defined such that it is not explicitly sensitive to size. Consistently, we see insignificant coefficients on a bank's total assets in the regression results for CoVaR, which include bank fixed effects. A bank's market share in the syndicated loan market has no measurable effect on CoVaR, either. Also the coefficient for market size is marginal and not statistically significant. Persistence in CoVaR is indicated by the highly significant and positive coefficients (around 0.5) on the one-quarter lagged CoVaR.

3.5.5 Exposure versus Origination

Our distance and interconnectedness measures are constructed based on loan origination during the prior 12 months. An alternative approach to calculate our interconnectedness measure is to calculate the portfolio overlap between any two banks using originations in the prior 48 months, which is the average maturity.

However, increasing the time-period over which we construct our interconnectedness measure might not increase the precision of our estimates. First, we construct the measure based on the mean/median maturity of syndicated loans but do not have information about changes in the maturity after origination (e.g. early repayment). Second, we do not have information related to changes in exposures after origination, for example, due to loan sales or hedging of exposures that we cannot observe. Moreover, from our analysis of the organizational structure in syndicated loans we know that financial institutions participate in syndicated loans with other financial institutions that have similar syndicated loan portfolios and thus repeatedly collaborate in syndications over time. Thus, we do not expect that the approximation of the syndicated loan exposures using 48 months differ substantially from our measure of syndicated loan origination.

As a robustness test, we construct our interconnectedness measure using the prior 48 month. We find that the correlation between this and the original measure using loan originations over the prior 12 months is more than 80% using both industry and regional aggregation. We then repeat all regressions for SRISK, DIP and CoVaR using the new measure. The results are very similar. Thus, loan originations in the prior 12 months is a good approximation of a bank's portfolio decision over the prior 48 months.

3.6 Conclusions

Loan syndication increases the overlap of bank loan portfolios and makes them more vulnerable to contagious effects. While banks seem to diversify by syndicating loans to other banks, it increases systemic risk of the financial system because banks become more similar to one another. To measure banks' interconnectedness in the form of common exposures, we develop a novel measure of loan market interconnectedness. Interconnectedness is driven mainly by bank diversification, less by bank size or overall loan market size. Using different market based measures of systemic risk, we find that interconnectedness is positively correlated with these systemic risk measures, and that such a positive correlation mainly arises from an elevated effect of interconnectedness on systemic risk during recessions.

Our results have several important implications for banks and regulators. First, market based measures are informative during bad times because they pick up fundamental risks of banks precisely in a moment when banks are worried about their counterparties' exposures.

Second, we provide an important link from balance sheet risk to market-based risk measures, i.e. common exposures to large syndicated loans. This is important for regulators. Knowing that common exposures to large corporate loans are an important contributor to systemic risk helps regulators to monitor the build-up of risk in the system. We provide a first step in the quantification of these exposures on the asset side of the balance sheet. Regulators with more detailed data can extend our analyses investigating and monitoring specific industry overlap, common exposures to leveraged loans or, for example, exchange rate risks that might be hidden in these loans.[43]

Third, an institution-oriented approach to assessing and limiting systemic risk exposure is insufficient as the narrative of the recent financial crises suggests. Banks do not internalize the risks they create for the financial system as a whole. The Bank of International Settlement (BIS) published an updated methodology to identify "Global Systemically Important Financial Institutions" (G-SIFIs) in July 2013 (BIS, 2013). The indicators to identify G-SIFIs comprise five factors: (1) bank size, (2) interconnectedness, (3) substitutability of services, (4) complexity, and (5) cross-border activity, each with an equal weight. While these factors include interconnectedness, its level is determined by a fixed 20% weight shared between aggregate liability and asset interconnectedness. We propose an additional commonality measure using large corporate loans as an additional indicator helping to identify G-SIFIS.

Fourth, the Financial Stability Oversight Council (FSOC), which was created in the U.S. following the Dodd-Frank Wall Street Reform after the 2008-2009 financial crisis, has the mandate to monitor and address the overall risks to financial stability. It has the authority to make recommendations as to stricter regulatory standards for the largest and most interconnected institutions to their primary regulators. We propose using interconnectedness through large corporate loans as part of FSOC's systemic risk oversight and monitoring system.

[43] The Thai financial crisis of 1997-1998 illustrates this. International banks made loans in U.S. dollar to Thai banks and these, in turn, lent to Thai firms in U.S. dollar to eliminate the exchange rate risks. After the devaluation of the Baht against the dollar, firms could not repay their U.S. dollar denominated debt and the Thai banks started to default on foreign lenders. Before the crisis, the exposure to Thai banks was identified as credit risk and the, at hindsight more important, (correlated) exposure to the Baht remained hidden.

3.7 Figures

Figure 3.1: Time Series of Market-Aggregate Interconnectedness, 1989-2011

This figure shows the time series of the monthly market-aggregate Interconnectedness from January 1989 to June 2011. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations in the U.S. syndicated loan market. Lender specialization in this figure is based on 2-digit borrower SIC industry. The market-aggregate Interconnectedness is an equal-weighted average of all U.S. bank's bank-level interconnectedness of all the lead arrangers. Three series of market-aggregate interconnectedness are shown below, and they employ equal-, size-, and relationship-weights at the lead arranger level, respectively. Grey shaded areas highlight NBER recession periods.

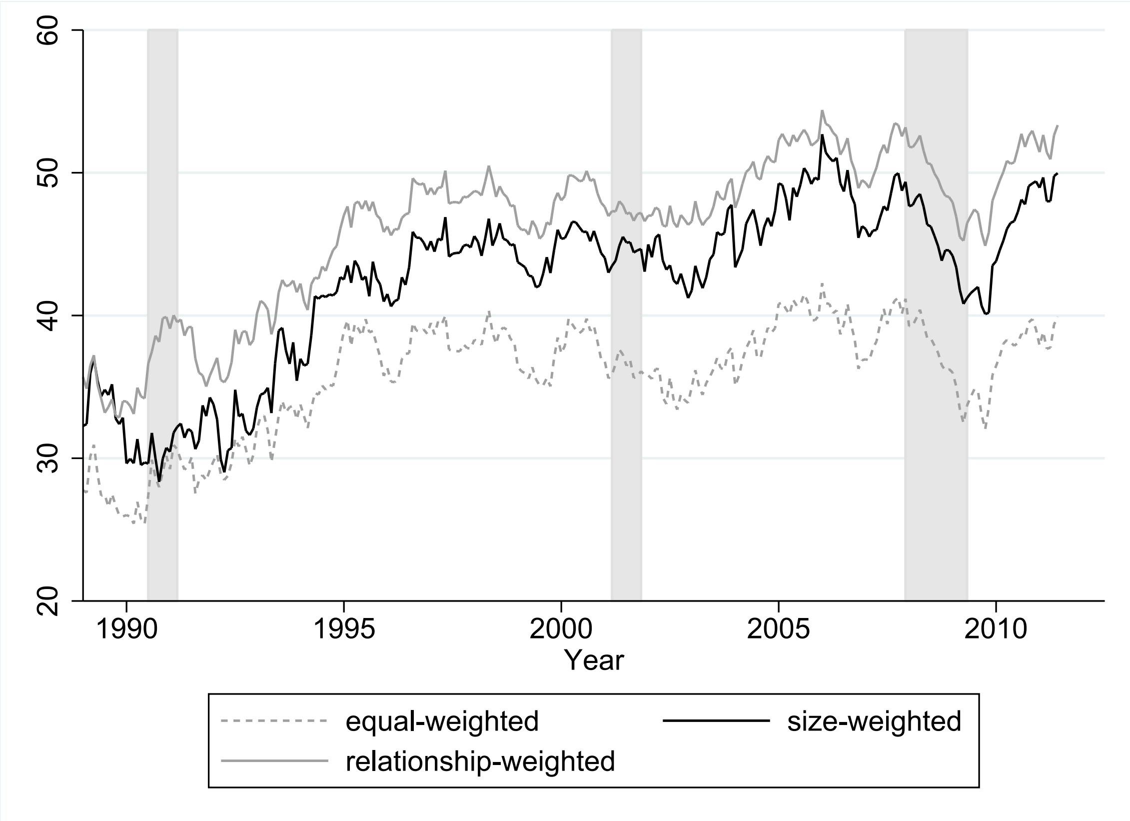


Figure 3.2: Time Series of Bank-Level Interconnectedness (I), 1989-2011

This figure shows the time series of the monthly bank-level Interconnectedness from January 1989 to June 2011. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations in the U.S. syndicated loan market. Lender specialization in this figure is based on 2-digit borrower SIC industry. Interconnectedness of a lead arranger is based on equal-weighting of distances to other lead arrangers. We select the time series for Bank of America and Morgan Stanley. The time series for Morgan Stanley starts in end-1996, when Morgan Stanley became active in the syndicated loan market. Grey shaded areas highlight NBER recession periods.

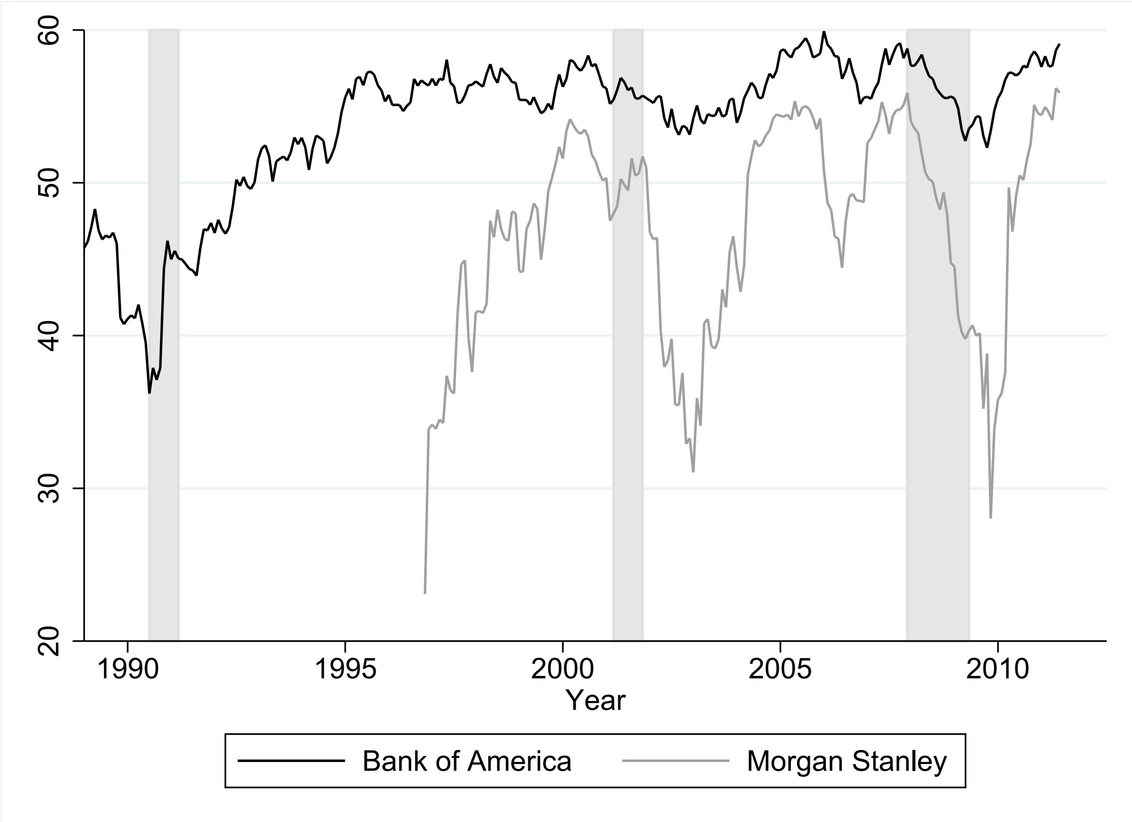
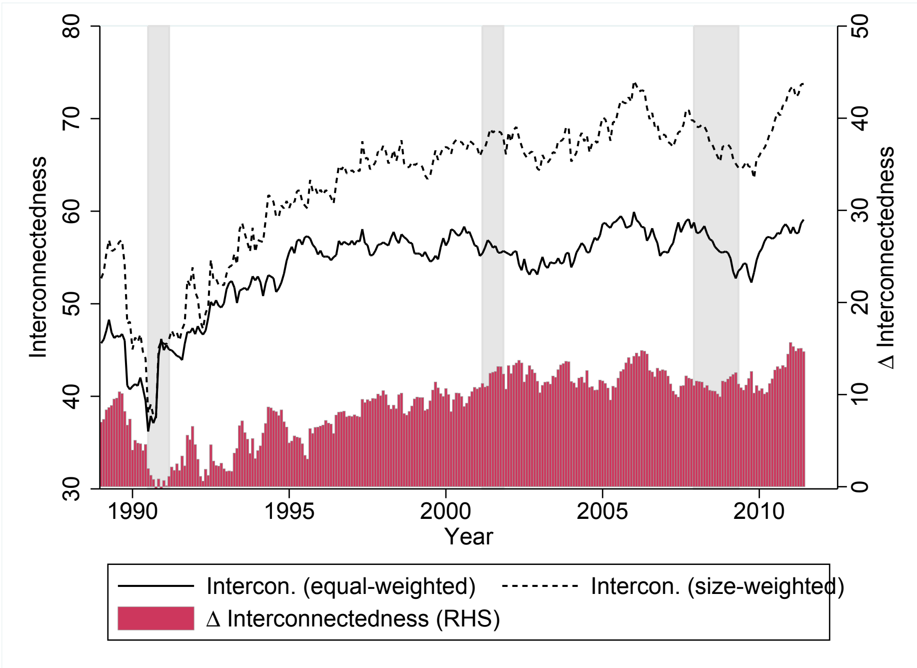


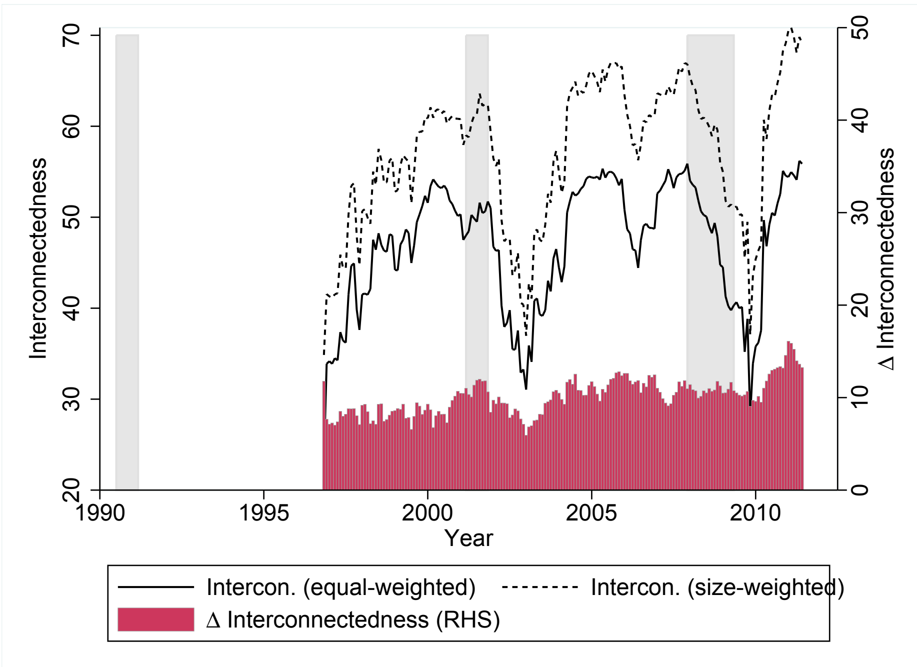
Figure 3.3: Time Series of Bank-Level Interconnectedness (II), 1989-2011

This figure shows the time series of the monthly bank-level Interconnectedness from January 1989 to June 2011. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations in the U.S. syndicated loan market. Lender specialization in this figure is based on 2-digit borrower SIC industry. Interconnectedness of a lead arranger is based on equal- and size-weighting of distances to other lead arrangers. We select the time series for Bank of America and Morgan Stanley. The time series for Morgan Stanley starts in end-1996, when Morgan Stanley became active in the syndicated loan market. The bars on the right hand side highlight the difference between the size-weighted and the equal-weighted bank-level interconnectedness over time. Grey shaded areas highlight NBER recession periods.

(a) **Bank of America**



(b) **Morgan Stanley**



3.8 Tables

Table 3.1: Variable Definitions

This appendix lists the variables used in the empirical analysis and their definitions.

Variable	Definition
Borrower Relationship	An indicator variable for whether a potential lender has previous relationships with the borrower
CoVaR	1% contagion value-at-risk of a U.S. bank measured in billions of U.S. dollars
DIP	Distressed insurance premium of a European bank in billions of euros
Distance	Distance between two banks based on their syndicated loan portfolios as lead arrangers
Diversification	Diversification of a bank based on its syndicated loan portfolio
Expansion	An indicator variable for whether a month falls into an expansion period, defined as a month not identified as a recession by the NBER
Interconnectedness	Bank-level interconnectedness
Interconnectedness Index	Market-aggregate interconnectedness
Lead Arranger Fixed Effect	Lead arranger (bank) fixed effect
Lead Relationship	An indicator variable for whether a potential lender has previous relationships with the lead arranger
Loan Facility Fixed Effect	Loan facility fixed effect
Market Share	Market share of a bank in the U.S. syndicated loan market based on the total loan amount the bank originated as a lead arranger
Market Size	The size of the U.S. syndicated loan market measured by the total newly originated syndicated loan amount in billions of U.S. dollars
Number of Specializations	Number of specializations a bank is engaged in as a lead arranger
Recession	An indicator variable for whether a month falls into recessions as identified by the NBER
SRISK	Systemic capital shortfall of a bank measured in billions of U.S. dollars
Systemic Risk	Any systemic risk measure
Syndicate Member	An indicator variable for whether a potential lender is chosen by the lead arranger to be a loan syndicate member
Total Assets	Book value of a bank's total assets in billions of U.S. dollars

Table 3.2: Summary Statistics

This table reports summary statistics of various distance, interconnectedness, and systemic risk measures as well as lead arranger (bank) and market characteristics. Distance between two lead arrangers is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations with regard to 2-digit borrower SIC industry and borrower U.S. state and can be equal-, size-, or relationship-weighted. Market-aggregate interconnectedness is the equally weighted average of all U.S. bank's bank-level interconnectedness for each month. Systemic risk of a lead arranger is measured by SRISK, DIP, and CoVaR. We show below summary statistics of the distance measures of 2,690,674 to 2,692,389 lead arranger pair-months, the bank-level interconnectedness measures of 26,277 to 26,741 lead arranger-months, the market-aggregate interconnectedness measure of 270 month, the SRISK measures of 5,733 lead arranger-months, the DIP measure of 1,343 lead arranger-months, and the CoVaR measures of 1,716 lead arranger-quarters. Lead arranger (bank) characteristics are reported of 27,117 lead arranger-months, and market characteristics are reported of 27 months.

Definition	N=	Mean	SD	10^{th}	50^{th}	90^{th}
Distance Measures:						
Distance in 2-digit Borrower SIC	2,692,389	0.630	0.222	0.320	0.664	0.898
Distance in Borrower State	2,690,674	0.634	0.229	0.313	0.672	0.917
Bank-Level Interconnectedness Measures:						
Equal-weighted Interconnectedness:						
Based on 2-digit Borrower SIC	26,741	36.1	14.0	16.1	37.8	54.0
Based on Borrower State	26,532	35.8	14.2	15.7	37.4	53.6
Size-weighted Interconnectedness:						
Based on 2-digit Borrower SIC	26,741	42.9	16.2	20.6	44.1	64.2
Based on Borrower State	26,532	43.5	16.7	20.3	44.9	65.0
Relationship-weighted Interconnectedness:						
Based on 2-digit Borrower SIC	26,483	46.7	17.2	23.0	48.0	69.1
Based on Borrower State	26,277	46.4	17.1	22.5	47.5	68.2
Market-Aggregate Interconnectedness Measures:						
Equal-weighted Interconnectedness:						
Based on 2-digit Borrower SIC	270	35.7	4.0	29.1	36.8	39.8
Based on Borrower State	270	35.3	4.7	28.3	35.8	41.1
Size-weighted Interconnectedness:						
Based on 2-digit Borrower SIC	270	42.4	5.8	32.2	44.1	48.7
Based on Borrower State	270	43.0	6.4	32.8	43.9	50.8
Relationship-weighted Interconnectedness:						
Based on 2-digit Borrower SIC	270	46.2	5.4	36.9	47.7	52.2
Based on Borrower State	270	45.9	5.6	36.8	46.4	52.8
Systemic Risk Measures:						
Systemic Capital Shortfall (SRISK) ($bn)	5,733	25.33	47.08	-7.29	5.96	88.72
DIP (EURbn)	1,343	14.70	18.51	0.51	6.54	42.15
1% CoVaR ($bn)	1,073	-18.23	34.32	-60.79	-2.75	-0.38
CATFIN (%)	252	28.25	12.93	14.72	25.46	44.70
Lead Arranger Characteristics:						
Total Assets ($bn)	17,341	310.48	475.56	10.02	118.02	844.97
Market Share as Lead Arranger (%)	27,117	1.00	3.24	0.00	0.08	1.80
# of Loans Arranged during 12 Months	27,117	47	129	1	8	107
$ of Loans Arranged during 12 Months ($bn)	27,117	9.08	35.90	0.04	0.55	15.72
Market Characteristics:						
Market Size ($bn)	270	912.82	504.64	234.91	956.13	1,657.64
Herfindahl	270	11.56	2.58	8.60	11.10	15.37

Table 3.3: Effect of Distance on Likelihood of Being Chosen As A Syndicate Member

This table reports coefficient estimates from regressions relating the likelihood of a potential lender (that was among the top 100 lead arrangers in the previous twelve months) being chosen as a syndicate member by the lead arranger to the distance between the potential lender and the lead arranger. The dependent variable is an indicator variable for whether the potential lender is indeed a syndicate member. The independent variable of interest is the distance between the potential lender and the lead arranger based on their portfolios of syndicated loans originated during the previous twelve months. We use distance as an independent variable based on lender specializations in borrower industry (2-digit borrower SIC industry) and borrower region (U.S. state), respectively. Control variables include an indicator variable for whether the potential lender has previous relationship with the lead arranger, an indicator variable for whether the potential lender has previous relationship with the borrower, and the market share of the potential lender as a lead arranger in the U.S. syndicated loan market during the previous twelve months. All regressions include loan facility fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Syndicate Member Indicator	Industry Aggregation	Regional Aggregation
Distance from Lead Arranger	-0.059***	-0.051***
	(0.0049)	(0.0040)
Previous Relationship with Lead	0.020***	0.022***
	(0.0020)	(0.0018)
Previous Relationship with Borrower	0.533***	0.534***
	(0.0105)	(0.0105)
Market Share as a Lead	0.004***	0.004***
	(0.0006)	(0.0006)
Loan Facility Fixed Effects	Yes	Yes
N =	10,887,311	10,887,313
Adjusted R^2	0.3231	0.3227

Table 3.4: Determinants of Interconnectedness

This table examines a number of bank characteristics as potential determinants of interconnectedness. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations with regard to 2-digit borrower SIC industry and borrower U.S. state and can be equal-, size-, or relationship-weighted. Bank characteristics include total assets (in billions of U.S. dollars), market size measured as syndicated loan originated during the previous twelve months in the U.S. syndicated loan market (in billion U.S. dollar), diversification, and the number of specializations the bank is engaged in. Panel A shows Pearson correlation coefficients between interconnectedness and bank characteristics, and Panel B reports results from multivariate regressions with lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

(a) **Pearson Correlation**

		Industry Aggregation			Regional Aggregation		
Pearson Correlation	N=	equal-weighted	size-weighted	relationship-weighted	equal-weighted	size-weighted	relationship-weighted
Total Assets	17,341	0.3014***	0.3402***	0.3263***	0.3782***	0.4001***	0.3871***
Market Size	26,532	0.2148***	0.2889***	0.2488***	0.2614***	0.3083***	0.2592***
Diversification	26,532	0.9772***	0.9547***	0.945***	0.9642***	0.9415***	0.932***
# of Specializations	26,532	0.729***	0.7345***	0.7361***	0.7599***	0.7591***	0.7602***

(b) **Multivariate Regressions**

	Industry Aggregation			Regional Aggregation		
Bank-level Interconnectedness	equal-weighted	size-weighted	relationship-weighted	equal-weighted	size-weighted	relationship-weighted
Total Assets	-0.000	0.001***	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Size	0.002***	0.004***	0.003***	0.002***	0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diversification	0.362***	0.396***	0.412***	0.346***	0.382***	0.392***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.007)	(0.006)
# of Specializations	0.141***	0.236***	0.288***	0.215***	0.346***	0.376***
	(0.011)	(0.013)	(0.017)	(0.020)	(0.028)	(0.029)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N =	17,341	17,341	17,248	17,341	17,341	17,248
Adjusted R^2	0.9723	0.9508	0.9524	0.9557	0.9293	0.9352

Table 3.5: Correlation between Systemic Risk and Interconnectedness

This table reports Pearson correlation coefficient estimates between a financial institution's systemic risk and its interconnectedness in the U.S. syndicated loan market as well as the U.S. financial sector's systemic risk and U.S. bank's market-aggregate interconnectedness in the U.S. syndicated loan market. Bank-level systemic risk is measured by systemic capital shortfall (SRISK) in billions of U.S. dollars, the monthly distress insurance premium (DIP) in billions of euros, and the opposite of 1% CoVaR in billions of U.S. dollars. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations with regard to 2-digit borrower SIC industry and borrower U.S. state and can be equal-, size-, or relationship-weighted. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

		Industry Aggregation			Regional Aggregation		
Pearson Correlation	N=	equal-weighted	size-weighted	relationship-weighted	equal-weighted	size-weighted	relationship-weighted
SRISK	5,733	0.1391***	0.1427***	0.1396***	0.2177***	0.2109***	0.2190***
DIP	1,343	0.2359***	0.2470***	0.2502***	0.2406***	0.2245***	0.2496***
-1% CoVaR	1,073	0.4178***	0.4246***	0.4252***	0.4502***	0.4607***	0.4594***

Table 3.6: Interconnectedness and SRISK

This table reports coefficient estimates from regressions relating a financial institution's SRISK to its interconnectedness in the U.S. syndicated loan market. The dependent variable is systemic capital shortfall (SRISK) in billions of U.S. dollars. The independent variable of interest is the interconnectedness of a lead arranger, which is computed based on its distance from all the other lead arrangers in specializations with regard to 2-digit borrower SIC industry and borrower U.S. state and can be equal-, size-, or relationship-weighted. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Expansion is an indicator variable equal to 1 if a month falls not into the recession periods identified by NBER. *Interconnectedness x Expansion* is the interaction term of Interconnectedness and Expansion. *Interconnectedness x Recession* is the interaction term of Interconnectedness and Recession. Control variables include the financial institution's total assets, market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, market size measured as syndicated loan originated during the previous twelve months in the U.S. syndicated loan market (in billion U.S. dollar), and one-month lagged SRISK. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. The bottom part of the table shows the hypothesis test (*H0: Interconnectedness x Recession – Interconnectedness x Expansion = 0*) and the hypothesis test's p-value. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Industry Aggregation			Regional Aggregation		
SRISK	equal-weighted	size-weighted	relationship-weighted	equal-weighted	size-weighted	relationship-weighted
Interconnectedness x Expansion	-0.006	-0.006	-0.001	0.001	-0.001	0.004
	(0.013)	(0.011)	(0.011)	(0.014)	(0.011)	(0.012)
Interconnectedness x Recession	0.061***	0.052***	0.050***	0.085***	0.072***	0.070***
	(0.022)	(0.018)	(0.018)	(0.021)	(0.018)	(0.017)
Recession	-1.287	-1.455*	-1.260	-2.146***	-2.343***	-2.149***
	(0.784)	(0.822)	(0.840)	(0.752)	(0.812)	(0.769)
Total Assets	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Share	-0.022	-0.022	-0.026	-0.026	-0.024	-0.030
	(0.113)	(0.113)	(0.113)	(0.115)	(0.115)	(0.117)
Market Size	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged SRISK	0.901***	0.901***	0.901***	0.898***	0.899***	0.898***
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N =	5,390	5,390	5,390	5,381	5,381	5,381
Adjusted R^2	0.9581	0.9581	0.9581	0.9591	0.9591	0.9591
H_0	0.067***	0.058***	0.051***	0.085***	0.073***	0.067***
p-value	0.003	0.002	0.005	0.000	0.000	0.000

Table 3.7: Interconnectedness and DIP

This table reports coefficient estimates from regressions relating a European financial institution's DIP to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the monthly distress insurance premium (DIP) in billions of euros. The independent variable of interest is the interconnectedness of a lead arranger, which is computed based on its distance from all the other lead arrangers in specializations with regard to 2-digit borrower SIC industry and borrower U.S. state and can be equal-, size-, or relationship-weighted. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Expansion is an indicator variable equal to 1 if a month falls not into the recession periods identified by NBER. *Interconnectedness x Expansion* is the interaction term of Interconnectedness and Expansion. *Interconnectedness x Recession* is the interaction term of Interconnectedness and Recession. Control variables include the financial institution's total assets, market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, market size measured as syndicated loan originated during the previous twelve months in the U.S. syndicated loan market (in billion U.S. dollar), and one-month lagged DIP. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. The bottom part of the table shows the hypothesis test (H0: *Interconnectedness x Recession – Interconnectedness x Expansion = 0*) and the hypothesis test's p-value. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Industry Aggregation			Regional Aggregation		
DIP	equal-weighted	size-weighted	relationship-weighted	equal-weighted	size-weighted	relationship-weighted
Interconnectedness x Expansion	0.002	0.023	0.012	-0.001	0.014	0.005
	(0.013)	(0.015)	(0.013)	(0.018)	(0.018)	(0.017)
Interconnectedness x Recession	0.130***	0.129***	0.105***	0.116***	0.110***	0.089***
	(0.038)	(0.036)	(0.030)	(0.033)	(0.031)	(0.026)
Recession	-2.725**	-2.629**	-2.378**	-2.778**	-2.724**	-2.303**
	(1.083)	(1.157)	(1.047)	(1.069)	(1.159)	(1.012)
Total Assets	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Market Share	1.302	1.325*	1.282	1.155	1.125	1.139
	(0.751)	(0.755)	(0.750)	(0.732)	(0.738)	(0.728)
Market Size	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged DIP	0.744***	0.743***	0.745***	0.747***	0.748***	0.748***
	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N =	1,325	1,325	1,325	1,316	1,316	1,316
Adjusted R^2	0.8291	0.8292	0.8289	0.8288	0.8288	0.8286
H_0	0.128***	0.107***	0.093***	0.117***	0.096***	0.084***
p-value	0.004	0.006	0.005	0.004	0.006	0.005

Table 3.8: Interconnectedness and CoVaR

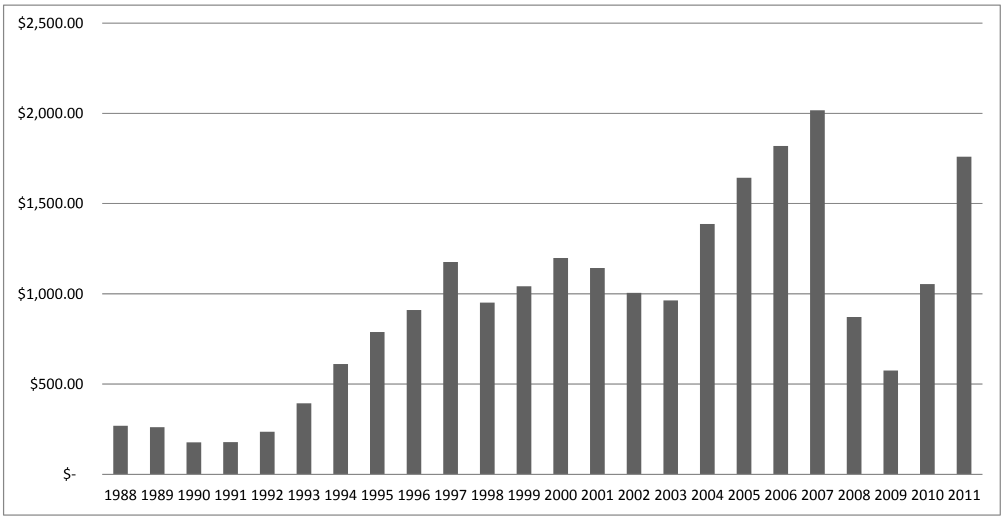
This table reports coefficient estimates from regressions relating a U.S. financial institution's CoVaR to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the opposite of 1% CoVaR in billions of U.S. dollars. The independent variable of interest is the interconnectedness of a lead arranger, which is computed based on its distance from all the other lead arrangers in specializations with regard to 2-digit borrower SIC industry and borrower U.S. state and can be equal-, size-, or relationship-weighted. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Expansion is an indicator variable equal to 1 if a month falls not into the recession periods identified by NBER. *Interconnectedness x Expansion* is the interaction term of Interconnectedness and Expansion. *Interconnectedness x Recession* is the interaction term of Interconnectedness and Recession. Control variables include the financial institution's total assets, market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, market size measured as syndicated loan originated during the previous twelve months in the U.S. syndicated loan market (in billion U.S. dollar), and one-quarter lagged CoVaR. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. The bottom part of the table shows the hypothesis test (*H0: Interconnectedness x Recession – Interconnectedness x Expansion = 0*) and the hypothesis test's p-value. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Industry Aggregation			Regional Aggregation		
-1% CoVaR	equal-weighted	size-weighted	relationship-weighted	equal-weighted	size-weighted	relationship-weighted
Interconnectedness x Expansion	0.008	0.001	0.012	0.022	0.020	0.021
	(0.027)	(0.021)	(0.020)	(0.026)	(0.023)	(0.024)
Interconnectedness x Recession	0.123*	0.098*	0.099*	0.152*	0.141**	0.125*
	(0.067)	(0.057)	(0.057)	(0.081)	(0.069)	(0.064)
Recession	-2.810	-2.923	-2.877	-3.320	-4.052	-3.556
	(2.209)	(2.303)	(2.289)	(2.437)	(2.741)	(2.601)
Total Assets	-0.010	-0.010	-0.010*	-0.010*	-0.010*	-0.010*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Market Share	-0.496	-0.494	-0.506	-0.505	-0.498	-0.513
	(0.701)	(0.701)	(0.703)	(0.704)	(0.701)	(0.703)
Market Size	0.002	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged CoVaR	0.519***	0.519***	0.519***	0.516***	0.514***	0.516***
	(0.081)	(0.081)	(0.081)	(0.082)	(0.082)	(0.082)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N =	1,035	1,035	1,035	1,029	1,029	1,029
Adjusted R^2	0.3177	0.3176	0.3175	0.3191	0.3195	0.3188
H_0	0.114	0.097	0.088	0.130	0.122	0.105
p-value	0.148	0.151	0.152	0.134	0.114	0.135

3.9 Appendix

Appendix A.3.1: The U.S. Syndicated Loan Market, 1988-2011

This appendix shows the size of the U.S. syndicated loan market by year from 1988 to 2011. Market size is measured by the total newly originated syndicated loan amount during the year in billions of U.S. dollars. Note that data for the year of 2011 is linearly projected based on the originated amount through June of that year.



Appendix A.3.2: Examples of Computing Distance between Lead Arrangers

This appendix shows how distance is computed by examples. Distance between two lead arrangers is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specialization in this appendix is based on borrower SIC industry division. We show below the computation of such distance among JPMorgan Chase (JPM), Bank of America (BAC), and Citigroup (C), which were the top three lead arrangers as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months. Note that distance is the key component for computing interconnectedness – the smaller the distance between two lead arrangers, the more interconnected they are.

SIC Industry Division (2-digit SIC Industries)	JPM (1^{st})	BAC (2^{nd})	C (3^{rd})	$(JPM - BAC)^2$	$(JPM - C)^2$	$(BAC - C)^2$
Agriculture, Forestry & Fishing (01-09)	0.03%	0.17%	0.00%	0.00000198	0.00000008	0.00000287
Mining (10-14)	5.10%	3.75%	4.77%	0.00018203	0.00001054	0.00010498
Construction (15-17)	2.34%	6.35%	0.31%	0.00160872	0.00041275	0.00365121
Manufacturing (20-39)	28.69%	23.35%	35.30%	0.00284811	0.00437535	0.01428362
Transportation, Communications, Electric, Gas & Sanitary	12.30%	12.02%	20.12%	0.00000753	0.00612126	0.00655812
Services (40-49) Wholesale Trade (50-51)	2.46%	3.82%	0.90%	0.00018570	0.00024177	0.00085125
Retail Trade (52-59)	6.81%	7.36%	2.83%	0.00003013	0.00159001	0.00205790
Finance, Insurance & Real Estate (60-67)	29.18%	30.71%	18.48%	0.00023371	0.01145803	0.01496453
Services (70-89)	13.09%	12.44%	17.18%	0.00004280	0.00166749	0.00224458
Public Administration (91-97)	0.00%	0.02%	0.11%	0.00000005	0.00000120	0.00000076
Total	100.00%	100.00%	100.00%	0.00514075	0.02587848	0.04471983
			Distance:	0.07169905	0.16086790	0.21147063

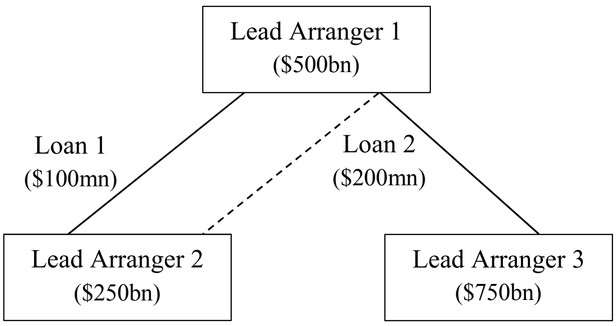
Appendix A.3.3: Distance among Top Ten Lead Arrangers

This appendix shows distance between any two top ten lead arrangers as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months. Distance between two lead arrangers is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specialization in this appendix is based on borrower SIC industry division. The top ten lead arrangers as of January 2007 were: JPMorgan Chase (JPM), Bank of America (BAC), Citigroup (C), Wachovia Bank (WB), Credit Suisse (CSGN), Deutsche Bank (DB), Royal Bank of Scotland (RBS), Goldman Sachs (GS), Barclays (BARC), and UBS (UBSN). Note that distance is the key component for computing interconnectedness – the smaller the distance between two lead arrangers, the more interconnected they are.

	JPM	BAC	C	WB	CSGN	DB	RBS	GS	BARC	UBSN
JPM	-									
BAC	0.07	-								
C	0.16	0.21	-							
WB	0.23	0.21	0.24	-						
CSGN	0.34	0.35	0.28	0.32	-					
DB	0.17	0.19	0.14	0.17	0.28	-				
RBS	0.30	0.34	0.19	0.29	0.30	0.20	-			
GS	0.25	0.28	0.13	0.19	0.26	0.16	0.18	-		
BARC	0.44	0.45	0.35	0.28	0.43	0.36	0.38	0.24	-	
UBSN	0.41	0.42	0.39	0.41	0.17	0.41	0.43	0.37	0.52	-

Appendix A.3.4: Example of Computing Weights among Lead Arrangers

This appendix shows how weights among lead arrangers in our bank-level interconnectedness measure are computed by an illustrative example. We use three kinds of weighting schemes: First, we assign equal weights to all other lead arrangers ("equal-weighted interconnectedness"). Second, we weight by size using a ratio of lagged total assets of lead arranger k over the sum of lagged total assets by all other lead arrangers ("size-weighted interconnectedness"). Third, we weight by contractual relationships based on the number of collaborative relationships of lead arranger i and lead arranger k relative to the total number of relationships of lead arranger i with all other lead arrangers ("relationship-weighted interconnectedness"). We show below an illustrative example comprising of three lead arrangers and two syndicated loans. Lead arranger 1 and 2 are leads in loan 1, which has a loan amount of $100mio. Lead arranger 1 and 3 are leads in loan 2, which has a loan amount of $200mio. In addition, lead arranger 2 is participant in loan 2. Lagged total assets for each lead arranger are in parenthesis.



The computations of lead arranger 1's weights ($x_{1,2,t}$ and $x_{1,3,t}$) in the computation of bank-level interconnectedness according to formula 2 (also shown below) are as follows:

$$\text{Interconnectedness}_{i,t} = \left(1 - \textstyle\sum_{k \neq i} x_{i,k,t} \cdot \text{Distance}_{i,k,t}\right) \times 100 \qquad (2)$$

	$x_{1,2,t}$	$x_{1,3,t}$
Equal-weighted:	½ (= 1/N, with N=2)	½ (= 1/N, with N=2)
Size-weighted:	¼ (= $250bn/($250bn+$750bn))	¾ (= $750bn/($250bn+$750bn))
Relationship-weighted:	2/3 (=2/(2+1))	1/3 (=1/(2+1))

Chapter 4

How do banks become interconnected? Evolution of syndicated loan structures and effects on loan pricing

4.1 Introduction

Over the last two decades, banks have become increasingly interconnected partly because of corporations' growing funding needs, both in size and complexity. The banking industry, however, is competitive by nature. As a result, banks face a fundamental question: Whom should they collaborate with while competing with the rest? If banks differentiate competitors by how similar they are in terms of lending expertise, i.e. our distance measure, the question translates into the following: Should banks collaborate with close or distant competitors? Our paper seeks to investigate this question by relating banks' lending expertise to the organizational form of loan syndicates and analyzes the implications for price collusion. More precisely, we study how banks form loan syndicates and analyze their implications on price collusion by addressing the following questions:[1] How do banks structure loan syndicates?[2] Whom do they choose as syndicate partners, and how are loan shares allocated? How does the organizational form of loan syndicates affect loan pricing, in particular price collusion? And, how does market concentration affect price collusion?

We focus on the effects of similarity in *lending expertise* among banks on syndicate formation, and loan pricing. Cai et al. (2018) provide a comprehensive look at the similarity

[1] Loan syndicates are ideal for the purpose of our paper. A syndicate consists of: (i) one or multiple lead arrangers that are delegated to screen/monitor the borrower and administer the loan/syndicate, and (ii) participant lenders whose main role is often just funding part of the loan. Lead arrangers choose whom to invite to join the syndicated loan and may delegate certain tasks to the senior members of the syndicate, e.g., co-leads, and co-agents. Thus, loan syndicates provide rich content about the interrelationships among lenders.

[2] We use "banks" to broadly refer to all types of financial institutions that are involved in the syndicated loan market, including commercial banks, investment banks, institutional investors, etc.

of two banks' loan portfolios by their *distance* measure between two banks. We extend their distance measure to the syndicated loan level (our novel lender distance measure) to capture the similarity in lending expertise of all lenders within a syndicate. We refer to syndicates with high similarity in lending expertise among lenders as "close" syndicates, and call syndicates "distant", if syndicate lenders' similarity in their lending expertise is low. Our lender distance measure therefore properly assesses the similarity, or closeness in lending expertise of lenders within a syndicated loan.

We hypothesize that lenders with higher similarity in lending expertise have lower production costs to produce borrower-specific information (Boot (2000)). Borrowers might benefit from improved screening and monitoring abilities of closer syndicates, if lead arrangers pass on some of these savings to the borrower. These cost savings might be particularly pronounced for loans with higher information asymmetries between the borrower and the lenders. We conjecture, that closer syndicates might reduce loan pricing for borrowers.

An alternative hypothesis is that improved information gathering by syndicates with higher similarity in lending expertise might enable lenders to "hold-up" borrowers due to higher information asymmetries between the borrower and outside lenders (Sharpe (1990), Rajan (1992)). Besides lower production costs resulting from higher similarity in their lending expertise, lenders often already possess borrower-specific and reusable information (Chan et al. (1986)). Also, these lenders with similar lending expertise might include alternative lead arrangers from the perspective of the borrower, potentially strengthening the "lock-in" effect. Consequently, we hypothesize that closer syndicates might collude on loan pricing to extract rents from the borrower.

We further hypothesize, that price collusion might be more pronounced during periods of low market concentration. As theoretically shown by Hatfield et al. (2017), in markets with syndication there exists a certain level of market concentration below which the scope for price collusion *increases* with reductions in market concentration. This mechanism results from an in-period punishment of lead arrangers, in that "price collusion can be sustained by a strategy in which firms [lead arrangers] refuse to join the syndicate of any firm [lender] that deviates from the collusive price." In the syndicated loan market, lead arrangers use confidential blacklists to exclude certain banks from syndicates.[3] We first investigate this hypothesis on a stand alone basis. Then, based on our "hold-up" hypothesis of close syndicates, we conjecture that price collusion during low market concentration might be particularly pronounced for close syndicates.

To investigate how lender distance affects the organizational form of loan syndicates and loan pricing, we empirically analyze the U.S. syndicated loan market, using Thomson Reuters LPC DealScan's loan origination data. We utilize a distance measure between pairs of banks to compute our distance measure on the similarity in lending expertise of lenders within a syndicated loan. We then compute measures of syndicate formation and

[3] According to anecdotal evidence, these blacklists are wide-spread in the U.S. syndicated loan market and regularly used by lead arrangers to punish lenders.

market concentration in the U.S. syndicated loan market.

First, we examine how lead banks structure syndicates. If lead arrangers structure a syndicate based on how similar lenders' lending expertise in the syndicate should be, the question translates into how lender distance affects the syndicate structure. We find that close syndicates are associated with smaller and more concentrated syndicates. That is, close syndicates consist of fewer lead arrangers, co-agents, and participants and have higher syndicate concentration (as measured by the Herfindahl index) compared to syndicates with higher lender distance. As discussed above, these closer syndicates might reinforce lenders ability for both improved screening and price collusion.

Second, we analyze how lead arrangers distribute the loan among syndicate lenders. That is, whom lead arrangers choose as members of the syndicate, and how lead arrangers allocate loan shares among the members. While choosing lenders with higher similarity in lending expertise into the syndicate might result in benefits from improved screening or price collusion, it might also increase competition for future syndicated loans from the borrower. Consistent with these trade-offs, we find that lead arrangers are more likely to choose either very close or very distant lenders for more senior roles (co-leads, co-agents) of the syndicate. In contrast, lead arrangers choice of participants becomes more likely with closer distance in lender expertise. Also, except for very distant syndicates, lead arrangers allocate higher loan shares to syndicate members across all loan roles once distance in lender expertise reduces. Consistent with lead arrangers reduced need to signal credit quality, or mitigate moral hazard, we find that lead arrangers do not retain higher loan shares in syndicates with high information asymmetries of the borrower once the syndicate distance is close. Consequently, similarity in lending expertise is an important factor determining the formation of loan syndication structures.

Third, we investigate how lenders similarity in lending expertise affects loan pricing. As discussed above, there exist potentially two opposing effects on loan pricing from syndicates with higher similarity in lenders' lending expertise. On the one hand, borrowers might benefit from lenders' improved screening and monitoring, as lead arrangers can pass on some of the cost savings to borrowers. On the other hand, hold-up of the borrower might lead to collusive loan pricing. Analyzing the *net* effect of these two opposing forces, we find that closer lender distance resulted in cheaper loan pricing until 2009 (consistent with improved screening), and more expensive loan pricing since 2010 (consistent with price collusion). Disentangling those opposite effects, we find strong evidence consistent with improved screening in close syndicates over the entire sample period, while price collusion only occurred since 2010.

Fourth and finally, we investigate the effect of market concentration on loan pricing. As discussed above, lower market concentration might enable lenders to collude on loan pricing. We first test the stand-alone effect of market concentration on loan pricing, and then interact our lender distance measure with different levels of market concentration to investigate their joint effect. We find that a reduction of market concentration below a certain level results in higher loan pricing. Further, when interacting market concentration with lender distance, we find that during periods of low market concentration price collusion only occurs for close syndicates.

The paper proceeds as follows. Section 4.1.1 provides a brief literature review and summarizes the contribution of our paper. In Section 4.2, we describe the institutional setup, and theoretical framework. In addition, we develop our syndicated loan distance measure. Data are described in Section 4.3 with summary statistics for our sample of syndicated loan facilities and the syndicated loan distance measure. Section 4.4 shows the empirical results of tests on our hypotheses on both of syndicate formation and loan pricing. Section 4.5 is conclusion.

4.1.1 Related Literature

We make several contributions to the existing literature. First, our paper is related to the growing literature on loan syndication. Among others, Chowdhry and Nanda (1996), Pichler and Wilhelm (2001), and Tykvova (2007) theoretically analyze the rationale for syndication and find that syndicates are formed for reasons such as risk sharing, knowledge transfer, and circumventing regulation. Empirical papers on syndicated loans have examined syndicate structure from the perspectives of information asymmetries (e.g., Lee and Mullineaux (2004), Jones et al. (2005), and Sufi (2007)), lenders' reputation (e.g., Dennis and Mullineaux (2000) and Gopalan et al. (2011)), corporate governance (e.g., Ferreira and Matos (2012)), and liquidity management (e.g., Gatev and Strahan (2009)). While this line of research has usually taken the organizational form of syndicates as given, recently member choice in loan syndicates has been studied (e.g. Sufi (2007), Cai (2010), Altunbas and Kara (2011)). This paper, to the best of our knowledge, is the first to examine syndicate structures from the perspective of the similarity in lending expertise among syndicate lenders and to study syndicate formation more broadly (beyond syndicate member choice).

Our paper is also related to the literature on syndicated loan pricing. Empirical papers have examined syndicated loan pricing from the perspectives of information asymmetry (e.g., Ivashina (2009), Cai (2010), Bharath et al. (2009)), liquidity (e.g., Gupta et al. (2008)), syndicated loan composition (e.g., Lim et al. (2014)), business cycle (e.g. Santos and Winton (2008), Santos (2010)), corporate governance (e.g., Ferreira and Matos (2012)), and pipeline risk (Bruche et al. (2017)). Our paper contributes to this literature by analyzing the effects of similarity in lending expertise among syndicate lenders and market concentration on loan pricing.

Finally, this paper is also related to studies in the industrial organization literature examining collusion. Among others, Nocke and White (2007) and Hatfield et al. (2017) theoretically analyze collusion in repeated extensive form games and show that under certain circumstances collusion can exist. For example, Hatfield et al. (2017) develop a model of syndicated markets with repeated interaction of lenders, in which low market concentration facilitates collusion. This resembles our result that price collusion of close syndicates occurs only during periods of low market concentration.

Also, collusion in syndicates has been widely discussed in the IPO market (e.g., Chen and Ritter (2000), Hansen (2001), and Abrahamson et al. (2011)). Our work provides empirical evidence of collusion in the syndicated loan market.

4.2 Setting, Theoretical Framework and Distance Measure

In this section, we first describe the institutional setup of syndicated bank lending. Then, we discuss the theoretical framework. Finally, we develop our new syndicated loan lender distance measure.

4.2.1 Institutional Setup

In this sub-section, we first provide a brief overview of the syndicated loan market. Then, we describe the syndication process. Finally, we highlight the key dimensions in which lead arrangers can affect the syndicate structure and the loan distribution to other banks.[4]

Syndicated Loan Market In a syndication two or more banks provide a loan to a borrower. Compared to bilateral loans, syndicated loans are usually more efficient to administer and cheaper. Consequently, annual total issuance volume in the U.S. market increased from $177bn in 1990 to $2,017bn in 2007, and quickly recovered from a drop during the Global financial crisis to $2,121bn in 2016. Also, almost all publicly listed firms in the U.S. use syndicated loans to borrow (e.g. Sufi (2007)), and with a median loan amount of $116mn individual syndicated loans are also large. Borrowing volumes from syndicated loans are larger than from public debt and equity issuance combined (Drucker and Puri (2007)). For banks, loan syndication is sizable too, with annual originated syndicated loan volume being 9.6% of total assets (Cai et al. (2018)).

While institutional investors engage in syndicated loans primarily based on risk-return considerations, banks consider the overall profitability of the borrower-creditor relationship. Moreover, lead arrangers also focus on the profitability of their creditor-creditor relationships. Specifically, in the syndication process lead arrangers possess a high leeway in structuring the syndicate and distributing the loan to other lenders, which might beneficially serve their own relationship to these creditors.

Syndication Process The syndication process follows two main stages. In the first stage, the issuer awards the mandate for the syndicated loan to a lead arranger. Mostly, borrowers invite their relationship banks and other banks to bid on the syndicate by outlining their pricing and syndication strategy. To determine loan pricing, each lead arranger performs an independent credit analysis of the borrower and creditors make bids. The issuer chooses the lead by awarding the mandate.

[4]The following discussion of syndicate formation maily follows Esty (2001) and Standard & Poor's *A Syndicated Loan Primer* (April 2016).

In the second stage, the lead arranger prepares an "information memorandum" describing the issuer and terms of the transaction for marketing the loan to other lenders. The document also contains information on compensation for lenders at different tiers (see below on details on different tiers), which come in the form of a spread over a base rate (e.g. LIBOR), and usually different kinds of fees (e.g. commitment fee, upfront fee). Using the "information memorandum", the lead arranger starts "book running" by contacting other banks and asking them for commitments to join the syndicate (see below on a discussion on the involved trade-offs). If total demand, in form of commitments, equals the target issue amount, the deal is "fully subscribed" and can be closed. If the total commitments are higher or lower than the target amount, the deal is "oversubscribed" or "undersubscribed", with syndicated loans being predominantly "oversubscribed". The lead arranger possesses different options to proceed, such as scaling back commitments, re-initiating to ask for commitments, scaling back the loan amount, and retaining a larger share itself in the loan. Once the lead arranger decides on the allocation of commitments, the syndication closes, lenders sign the final loan document, and funds are transferred to the borrower.

Consequently, lead arrangers possess significantly leeway during the syndication process to affect both the syndicate structure as well as loan shares to other syndicate lenders.

Syndicate Structure With respect to syndicate structure, lead arrangers can decide whether to allocate monitoring and administrative tasks to other banks, or to structure, administer, and distribute the loan itself. For example, an 'administrative agent' monitors the loan and handles interest and principal payments, or a 'documentation agent' chooses a law firm and handles documentation. These "joint mandates" usually also increase the chance of a successful syndication, as lenders in more senior roles often commit to larger loan shares and might support loan distribution. Successful syndication might consequently also be a motive by the borrower to request "joint syndication" himself.

In addition, lead arrangers face an important trade-off when deciding on the size of the syndicate. On the one hand, smaller syndicates provide benefits to the borrower in the form of greater confidentiality, concentrated voting control, and administrative convenience. For lenders, smaller syndicates result in greater revenues, and increased influence to modify loan terms over the life of the loan. On the other hand, larger syndicates provide benefits to the borrower as competition usually increases among bidding lenders, which can reduce loan pricing and increase the chance of successful syndication. The lead arranger might benefit due to higher underwriting fees from other lenders to compensate his increased syndication efforts, and from not having to disappoint otherwise excluded bidding lenders. Participating lenders might benefit in meeting their diversification objective and by receiving easier approval in the lender's internal credit application process.

Loan Distribution With respect to loan distribution, lead arrangers also possess high leeway to decide, which banks join the syndicate and at which tiers. Lead arrangers usually allocate more senior roles in the syndicate to its own relationship banks to strengthen their relationship by rewarding them with higher fee compensation. Also, lenders in more senior roles are selected based on lenders experience in lending to specific industries or regions. Finally, lead arrangers might follow borrowers request to reward other of the borrower's relationship banks to more senior roles. Otherwise, lenders obtain the status of participant lenders, whose main role is often just funding part of the loan.

Finally, lead arrangers also possess leeway in the allocation of loan shares. Allocating higher loan shares to lenders in more senior roles can also reward lead arrangers relationship banks by increasing their revenues from interest payments and fees. Also, borrowers might also ask the lead arranger to invite other borrower relationship banks into the syndicate. Lead arrangers might want to reduce their loan shares for more risky loans, which might however conflict with agency considerations. Specifically, lead arrangers can mitigate adverse selection by holding a larger loan share to credibly signal the loan quality. In addition, a larger loan share also incentivizes lead arrangers ex-post monitoring of the loan, which can mitigate the impact of moral hazard. Allocating a higher loan share to lenders in more senior roles in the syndicate can similarly mitigate agency considerations, and increase incentives to pool borrower screening and monitoring expertise of more senior lenders.

4.2.2 Theoretical Framework

In this sub-section, we outline the theoretical framework for analyzing the role of syndicated loan lender distance and market concentration on loan pricing. First, we describe the economic mechanisms underlying loan pricing. Second, analyzing this framework we provide a number of testable hypotheses.

Effects of Close Syndicates: Improved Borrower Screening

The theoretical literature on banking relationships views borrower-lender relationships as a mechanism, in which lenders produce borrower-specific information that is durable and reusable over time (Boot (2000)). Close syndicates consist of lenders with higher similarity in their lending expertise (compared to lenders in more distant syndicates). Collectively, lenders in close syndicates might thus more effectively produce borrower-specific information, both during the due diligence and monitoring phases of evaluating a borrower. Also, lenders often syndicated loans to the same borrower, so that lenders already possess borrower-specific and reusable information (Chan et al. (1986)). Close syndicates are also more likely to pool information. Further, lead arrangers might pass on some of the benefits from improved screening and monitoring to the borrower, thereby lowering loan pricing. This leads to the following hypothesis on the effect of lender distance on loan pricing:

HYPOTHESIS 1: *Lenders are more likely to reduce loan pricing if syndicates become closer.*

Effects of Close Syndicates: Price Collusion

An alternative hypothesis is that improved information gathering by close syndicates, borrowers might be more inclined to be "locked-in" into such syndicates (see Sharpe (1990), and Rajan (1992)). If borrowers are locked-in, lenders will be more likely to extract rents. This leads to the following hypothesis:

HYPOTHESIS 2: *Lenders are more likely to increase loan pricing if syndicates become closer.*

Importantly, hypotheses 1 and 2 are not mutually exclusive. Close syndicates might be able to have lower production costs for borrower screening and monitoring, but at the same time also increase loan pricing due to hold-up of the borrower. In our empirical analysis, we first test the *net* effect of hypotheses 1 and 2, and then try to separate these two opposing effects.

Low Market Concentration: Higher Scope for Price Collusion

The theoretical literature on loan pricing in syndicates shows that lower market concentration fosters price collusion (Hatfield et al. (2017)).[5] Specifically, in markets with syndication there exists a certain level of market concentration below which the scope for price collusion *increases* with reductions in market concentration. This mechanism results from an in-period punishment of lead arrangers, in that "price collusion can be sustained by a strategy in which firms [lead arrangers] refuse to join the syndicate of any firm [lender] that deviates from the collusive price." The authors show that this punishment strategy becomes more forceful in markets with lower market concentration.[6] This leads to the following hypothesis:

HYPOTHESIS 3: *Below a certain level of market concentration, price collusion increases with reductions in market concentration.*

Taken together, our two hypotheses 2 and 3 predict that price collusion should be most pronounced during periods of low market concentration for loans originated by closer syndicates. In our empirical analysis, we first test hypothesis 3 on a stand alone basis, and then test for the joint effect of hypotheses 2 and 3.

4.2.3 Lender Distance Measure

In this sub-section, we develop our key explanatory variable to measure the similarity, or closeness in lending expertise of lenders within a syndicated loan, namely our lender

[5] Hatfield et al. (2017) motivate their theory by observations of investment banking fees for initial public offerings (IPOs), which are also syndicated.

[6] According to anecdotal evidence, lead arrangers in the syndicated loan market regularly punish banks by adding them to confidential blacklists that exclude them from syndicates.

distance measure.

4.2.3.1 Distance between two lenders

The key intermediate measure to compute our lender distance measure, is the distance between two lenders measure developed in Cai et al. (2018). This measure captures the similarity in the syndicated loan portfolios of two lenders, which we use as a measure for the similarity in lending expertise between these two lenders.

To compute the syndicated loan portfolio of an individual lender in a given month, we compute each lead arranger's total originated loan facility amount during the prior 12 months.[7] Next, we compute each lead arranger's portfolio weights in lending specialization related to borrower industry, using the 2-digit borrower SIC-industry.[8] Let $w_{s,j,t}$ be the weight (share) that lead arranger s invests in industry j during the 12 months prior to month t.[9]

Using these lending specializations, the distance between two lenders is computed as the Euclidean distance between those two lenders in the J-dimensional space as

$$distance_{s,k,t} = \frac{1}{\sqrt{2}}\sqrt{\sum_{j=1}^{J}(w_{s,j,t} - w_{k,j,t})^2} \tag{4.1}$$

where distance$_{s,k,t}$ is the distance in lending specialization between lender s and lender k in month t, with $s \neq k$. The distance measure ranges between zero and unity, with a smaller distance indicating a higher similarity in the two lenders' lending expertise.

4.2.3.2 Syndicated loan lender distance

Next, we compute our syndicated loan lender distance measure. Suppose in syndicate i are N_i pairs of lead arranger(s) and other syndicate members. The syndicated loan lender distance is the average distance of these N_i pairs of lead arranger-lender in the 12 months prior to the loan origination month t. Let $Distance_{i,t}$ denote the lender distance in syndicate i that is arranged in month t. Then

$$Distance_{i,t} = \frac{1}{N_i} \cdot \sum_{n=1}^{N_i} distance_{s^n,k^n,t} \tag{4.2}$$

where $distance_{s^n,k^n,t}$ denotes the distance between the n^{th} pair of lead arranger s^n and syndicate member k^n in month t, where $s^n \neq k^n$.

Note that the lender distance measure centers on the similarity in lending expertise from the viewpoint of the lead arranger(s), and thus excludes distance pairs among non-lead syndicate members. Thus, for syndicates with more than two lenders, lender distance can

[7] Loan amounts are split equally across all lead arrangers in the loan, if a loan has multiple leads.

[8] Also, we examine lending specialization related to borrower region (using 3-digit borrower zip code), and obtain very similar results.

[9] Industry weights across J industries for each lead arranger i sum up to unity ($\sum_{j=1}^{J} w_{s,j,t} = 1\ \forall t$).

differ even within the same set of lenders in the same originating month. Also, note that the lender distance measure captures the similarity in lending expertise during the prior 12 months to the loan origination month t. Consequently, the same syndicate structure can exhibit varying distances over time, depending on the evolution of the similarity in lending expertise of the lenders in the syndicate.

In Appendix Table A.4.2, we show a computational example of the syndicated loan lender distance.

4.3 Data and Summary Statistics

In this section, we first briefly describe our data. Then, we describe the classification of lender roles and provide summary statistics regarding lenders, borrowers, and syndicated loan facilities. Finally, we discuss our new loan lender distance measure.

4.3.1 Data

Our primary data source is a sample of syndicated loans from Thomson Reuters LPC Dealscan, which contains information on loan contract terms, borrower characteristics, lender roles, syndicate structure, and loan distribution. Dealscan contains a fairly complete coverage of syndicated loans, especially for the U.S. market. Our original data set contains 127,040 syndicated loans to 31,927 firms originated from a total of 1,299 lead arrangers during January 1988 to March 2017. To focus our analysis and make the computation of our loan lender distance measure manageable, we follow the literature and restrict our sample to larger lead arrangers so that on average lead arrangers in our sample annually originate one percent of syndicated loans in the market.[10] Our final sample contains 123,752 syndicated loans to 30,722 U.S. firms from January 1988 to March 2017 that were originated by 223 lead arrangers.

Importantly, these 223 lead arrangers also frequently obtain less senior roles in the syndicate so that 95.2% of the syndicate's co-agents and 77.2% of the syndicate's participants are covered in the sample.[11] These high coverages are consistent with lead arrangers in the syndicated loan market regularly engaging in reciprocal lending arrangements as documented by Cai (2010). That is, lead arrangers also regularly serve in less senior roles in syndicates, where their participant lenders led the syndicate. The non-covered participants in our sample are mostly foreign banks, or smaller domestic financial institutions that do not (or at most sporadically) originate syndicated loans in the U.S. market. Consequently, our sample contains a fairly high coverage of lenders across different lender roles to investigate syndicate formation.

We show in this paper that the average lender distance in a syndicated loan is much smaller than the average lender distance between two randomly selected lenders. In other

[10]For consistency of the distance measure, the selection of lead arrangers follows Cai et al. (2018).
[11]In Appendix A.4.3 we provide details on the classification of lender roles.

words, lead arrangers actively choose lenders that have similar lending expertise as themselves. Thus, participants covered in our sample represent those that are also more likely to be selected into syndicates.

To obtain richer financial information on individual borrowing firms, we link our syndicated loan data to Compustat using matchings from Chava and Roberts (2008), Schwert (2017), and Cai et al. (2018). Through this matching, we retrieve borrower financial data for up to 48,317 syndicated loans (39% of the sample).

4.3.2 Summary Statistics

Table 4.1 shows summary statistics. Panel A of Table 4.1 presents lead arranger characteristics. The sample contains 33,861 unique lead arranger-months. On average, a lead arranger has a market share of 1% during the prior 12 months, in which 65 syndicated loans with a total volume of $11.3 billion were arranged. Four out of five lead arrangers (82%) are banks (as opposed to finance companies, institutional investors, etc.) and hence are considered having expertise in screening, monitoring, and relationship lending. Consequently, most lenders in the syndicated loan market constitute competitors for a lead arranger, when deciding on syndicate formation.

Panel B of Table 4.1 presents borrower characteristics, which are reported based on the time of loan origination. An average borrowing firm in our sample has sales of $3.54 billion at loan closing. 38% of loans are first syndicated loans of the borrower in the syndicated loan market in our sample period, while the average number of previous syndicated loans is 4.1. Among borrowers whose firm type is known, 64% are identified as private firms, and 36% as public firms. Among the borrowers with Compustat data, the average book value of total assets is $12.3 billion, the average book leverage ratio is 37%, the average earnings to asset ratio is 6%, 56% have an S&P debt rating, and 29% have an S&P investment-grade debt rating.

Panel C of Table 4.1 reports loan characteristics. The average syndicated loan facility is $271 million, with a loan maturity of 50 months. About one-third (34%) of loans are classified as term loans. The average interest rate spread on drawn funds is 252 basis points over LIBOR. The most common loan purpose is working capital and corporate purposes (72%), followed by acquisitions (22%), refinancing (18%), and backup lines (5%), where a loan facility can have multiple loan purposes.

Importantly for our analysis, DealScan provides rich information on the syndicate structure and loan distribution. On average, a syndicated loan has 6.0 lenders, splitting into 1.6 lead arrangers, 1.3 co-agents, and 3.2 participants. To measure the concentration of a syndicate, we compute the Herfindahl index as the sum of squared individual loan shares of syndicate lenders.[12] We also report summary statistics of loan shares, which are computed as the average among the lender group if there is more than one in the syndicate. On average, lead arranger(s) retain 31.4% of the loan, 14.7% are held by co-agents, and 14.7%

[12] The Herfindahl index ranges between zero and one, where one being most concentrated (a single lender holding 100% of the syndicated loan).

are also held by participants. Importantly for our analysis on syndicate formation, these variables on syndicate structure and loan distribution show a high degree of variation. Compared to the summary statistics on syndicate structure reported by Sufi (2007) for the period from 1992 to 2003, on average, the total number of lenders in the syndicate has shrunk, loan shares of lead arrangers increased, and consequently syndicate concentration also increased.

Finally, Panel D of Table 4.1 reports summary statistics of the market concentration of the syndicated loan market. On average, the Herfindahl index of market concentration is 0.11, which indicates an "unconcentrated market" based on the definition of the U.S. Department of Justice.[13] As shown in Figure 4.2, the market concentration varied over time, with about a tenth of months constituting a "moderately concentrated" market (greater or equal than 0.15) and also a moderate degree of variation in the "unconcentrated market" range.

In Appendix Table A.4.1, we list the variable definitions.

4.3.3 Lender Distance Measure

For the sub-sample where we are able to compute lender distant pairs, we construct our new syndicated loan lender distance measure. As discussed above, this measure captures the similarity in lending expertise of the lead with the lenders in the syndicate, and ranges between zero and one. Figure 4.1 shows that lender distance declined over time, indicating that the similarity in lending expertise of lenders within a syndicate increased over time. In other words, on average lenders in syndicates became closer competitors to the lead arranger over time. To ensure that this time-trend does not affect our results, we carefully control for year fixed effects in our regressions.[14] As shown in Panel C of Table 4.1, on average, the lender distance of a syndicated loan is 0.29, which is less than half of any randomly selected lender pair of 0.61 (see Panel A of Table 4.1).[15] This finding provides indicative evidence that similarity in lending expertise might be an important factor in syndicate formation. Finally, the lender distance measure has a standard deviation of 0.14, implying that there is sufficient variation in the data for the empirical analyses.

Table 4.2 lists the top three lead arrangers for close, mid, and distant syndicates from 2014 to 2016 by classifying lender distance into the lowest, middle, and highest one-third of the originating month of the syndicate. The top three lead arrangers (Bank of America, JPMorgan Chase, and Wells Fargo) are identical across close, mid, and distant syndicates, even in their ranking. This provides evidence that a lead arranger regularly forms syndicates with different lender distances, indicating that lead arrangers can actively decide on the similarity in lending expertise of the lenders it chooses to include in a

[13]See https://www.justice.gov/atr/horizontal-merger-guidelines-08192010

[14]In our analysis on 'loan pricing and market concentration' (Table 4.9), we include three-year fixed effects as otherwise most of the variation in the market concentration measure would be absorbed by year fixed effects.

[15]Note that the computation of the distance between two lenders measure is completely identical as in Cai et al. (2018). Consequently, also summary statistics in our longer sample period are very similar.

syndicate. Also, concentration of lead arrangers is most pronounced for close syndicates, with the top three lead arranger arranging 43% of close syndicates (compared to 32% for distant syndicates, and 17% for mid syndicates).

4.4 Empirical Analysis

In this section, we first analyze how distance among lender pairs and syndicated loan lender distance affects syndicate formation. Next, we show how borrower and loan characteristics differ across different degrees of syndicated loan lender distance and show their syndicate formation characteristics. Finally, we test our hypotheses by investigating how syndicated loan lender distance and market concentration affects loan pricing.

4.4.1 Distance and Syndicate Formation

In this sub-section, we examine how lead banks structure syndicates. If lead arrangers structure a syndicate based on how close or distant competitors are who it wants to join the syndicate, the question translates into the following: How does lender distance affect the syndicate structure? As outlined in the introduction and the institutional setting, choosing close competitors can have both positive effects (e.g., improved screening) and negative effects (e.g., price collusion among lenders) to the borrower. Syndicate structure might influence the magnitude of these effects. Smaller and more concentrated syndicates increase lenders stake in the loan, which should reduces moral hazard and align incentives among lenders for better screening and monitoring. However, smaller and more concentrated syndicates might also reduce price competition among lenders, and foster price collusion. In addition, assigning lenders into more senior syndicate roles might also reinforce these effects, as it mitigates lenders moral hazard and gives lenders a larger share in the proceeds from the syndicate.

We seek to find supporting evidence consistent either with hypothesis 1 or 2. The general regression specification we test is

$$Synd_{i,t} = \alpha + \beta_1 \cdot Distance_{i,t} + \beta_2 \cdot Distance^2_{i,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t} \tag{4.3}$$

where the dependent variable $Synd_{i,t}$ are different measures of syndicate structure, such as the number of lenders, the number of lead arrangers, the number of co-agents, the number of participants, and the concentration of the syndicate (Herfindahl). The key right-hand-side variables $Distance_{i,t}$ and $Distance^2_{i,t}$ measure the (squared) syndicated loan lender distance of syndicate i originated in month t. We allow ex-ante for a non-linear relationship of $Distance_{i,t}$ to capture the possibly non-linear net effect from the following two opposing forces. On the one hand, choosing lenders with higher similarity, or closeness in lending expertise into the syndicate might reduce production costs due to improved screening, or increase revenues from price collusion. On the other hand, choosing closer competitors into the syndicate might increase competition for future syndicated loans from the borrower.

Either of these two forces might dominate the net effect at different levels of lender distance. The control variables ($X_{i,t}$) are consistent to the ones used in the literature (such as in Sufi (2007)), and include various borrower characteristics, loan characteristics as well as year, industry, state, loan purpose, and interest type fixed effects. Standard errors are heteroscedasticity robust and clustered by borrower 2-digit SIC industry.

Table 4.3 reports the results. While we think of lead arrangers having an intention to form closer or more distant syndicates, we only observe the ex-post realized distance in loan syndicates. Consequently, our results on syndicate formation display correlations between our lender distance measure and the syndicate structure. In all regressions on the number of lenders, leads, co-agents, and participants, the estimated coefficients reveal a concave relationship of our distance measure that is significant at the 1% level. Consistent with our conjecture of the above discussed opposing forces, we find that the number of syndicate lenders (and the number of lenders across all roles) slightly reduces for very distant syndicates and strongly reduces for mid and close syndicates (see Figure 4.3 (a)).[16] These effects are also economically significant. For example, as reported in column (1), a syndicate with a loan lender distance being one standard deviation lower than the median is associated with on average 5 fewer lenders in the syndicate (or -83% at a mean of 6.04 lenders). Consistent with the importance of more senior roles for improved screening and price collusion, the economically strongest difference in the number of syndicate members results from fewer participants.

Analyzing the effect of lender distance on syndicate concentration (Herfindahl) shows similar results (column (5)), with lender distance having a convex effect on syndicate concentration (see Figure 4.3 (b)). That is, while syndicate concentration reduces for closer lender distance in very distant syndicates, syndicate concentration increases for closer lender distance in mid and close syndicates. In terms of magnitude, a syndicate with a one standard deviation lower lender distance than the median syndicate is associated with a higher concentration of the syndicate by 0.05 (or 20% at a mean Herfindahl of 0.27).

4.4.2 Distance and Loan Distribution

Next, we analyze how lead arrangers distribute loans to other syndicate lenders. As discussed in the institutional setting above, loan distribution consists of choosing syndicate members and allocating loan shares. That is, we address the questions of whom lead arrangers choose to let into the syndicate? And, among those chosen syndicate members, how do lead arrangers allocate loan shares?

4.4.2.1 Syndicate Member Choice

First, we examine lead arrangers choice of syndicate members. We seek to find supporting evidence consistent with hypotheses 1 or 2, in that lead arrangers might choose lenders

[16] Note, median (mean) lender distance is 0.26 (0.29), and the centered 80% interval ranges from 0.15 to 0.47. One standard deviation of lender distance is 0.14.

with similar lending expertise to either delegate screening and monitoring responsibilities within the syndicate, or collude on loan pricing. Utilizing the distance measure between two banks, we measure the degree of similarity in lending expertise between the lead arranger and potential syndicate members. We separately investigate lead arrangers choice of co-lead arrangers, co-agents, and participants. The general regression specification we test is

$$Member_{s,k,i,t} = \alpha_i + \beta_1 \cdot distance_{s,k,t} + \beta_2 \cdot distance^2_{s,k,t} + \gamma_1 \cdot RELL_{s,k,t} + \gamma_2 \cdot RELB_{k,i} + \gamma_3 \cdot MS_{k,t} + \varepsilon_{s,k,i,t} \tag{4.4}$$

where the dependent variable $Member_{s,k,i,t}$ are different indicator variables that equal one if lead arranger s chooses lender k in a specific role in loan syndicate i that is originated in month t. Lender roles are co-lead arranger, co-agent, and participant. Linking this analysis to our previous investigation on syndicate structure above, we exclude syndicates in which lead arrangers decided not to assign lenders into these roles.[17] Also, as lead arrangers usually start by assigning lenders to more senior roles, we exclude lenders that are chosen in more senior roles from the choice set of loan membership for less senior roles such as participants.[18]

The key independent variable is $distance_{s,k,t}$ (and $distance^2_{s,k,t}$), measuring the (squared) distance between lead arranger s and lender k in the 12 months prior to month t. Thus, $distance_{s,k,t}$ measures whether lead arrangers choose lenders with close or distant similarity in lending expertise into the syndicate. Consistent with the discussions above, we also allow for a non-linear relationship of $distance_{s,k,t}$ on syndicate member choice. We control for loan facility fixed effects, to rule out any facility-specific effects, such as borrower characteristics, lead arranger characteristics, time-specific effects, and loan characteristics. In addition, we also control for the effects of prior relationships between the lead arranger and lender as well as prior relationships between the potential syndicate member and the borrower. Specifically, $RELL_{s,k,t}$ is an indicator variable for whether lead arranger s syndicated a loan with lender k prior to month t (no matter what roles the two lenders took). $RELB_{k,i}$ is an indicator variable for whether lender k syndicated a loan to the syndicate's borrower prior the originating month of syndicate i (no matter what role it took). In addition, we include the market share of lender k in the 12 months prior to month t ($MS_{k,t}$) to proxy for lender k's reputation, market size, lending capacity, or power in the syndicated loan market. Standard errors are heteroscedasticity robust and clustered by lead arranger.

Table 4.4 reports the results. In all regressions, the estimated coefficients on the distance measure show a convex relationship that is significant at the 1%-level. Consistent with our hypotheses on improved screening and price collusion of close syndicates, the propensity to be chosen as syndicate member increases for closer (compared to mid) syndication. At

[17] E.g., syndicates without a co-lead arranger are excluded in the regression for co-lead arranger choice
[18] Our results are very similar without restricted choice sets.

the same time, the likelihood of being selected as syndicate member increases for distant (compared to mid) syndicates, consistent to our conjecture of lead arrangers avoiding future competition for the same borrower. However, there is an important difference between these convex relationships across different lender roles. For the selection of co-leads (column (1)), lead arrangers are much more likely to choose more distant (compared to mid) competitors, and to some degree also very close competitors (see Figure 4.4 (a)).[19] Lenders with a one standard deviation higher distance between the lead arranger and the lender compared to the median are associated with a higher likelihood of being chosen as co-lead by 3.0%-points. In comparison, lenders at the 25th-percentile (compared to the 10th-percentile) of distance between the lead arranger and the lender have a higher likelihood of being chosen by 1.0%-point. The results on the selection of co-agents are very similar (column (2)). These findings on the selection of co-leads and co-agents are consistent with the trade-off between the benefits of lower production costs and price collusion of selecting close lenders, and the benefit of reduced future competition when selecting distant lenders.

In contrast to the results for co-leads and co-agents, lead arrangers predominantly prefer to choose participant lenders with more similar lending expertise (see column (3) and Figure 4.4 (b)). Consequently, lead arrangers select participant lenders that reinforce improved screening and price collusion. The estimated control variables provide consistent results.

4.4.2.2 Allocation of Loan Shares

Next, we investigate how the lead arranger allocates loan shares among the lenders in the syndicate. Again, we aim to investigate whether lead arrangers allocate higher loan shares to closer syndicates to align incentives for improved screening or price collusion (hypothesis 1 or 2), or allocate higher loan shares in more distant syndicates to reduce future competition. Specifically, we analyze how the allocation of loan shares to lenders with different roles (lead, co-agent, and participant) varies across syndicates. As multiple lenders with the same role in a syndicate cannot be considered as independent observations, we compute the average loan share for each role across possibly multiple lenders of that role to avoid understating standard errors.[20] To investigate the allocation of loan shares across syndicates, we estimate regression specification (4.3) as discussed above, except for using loan share as dependent variable.

Table 4.5 reports the regression results. In all regressions, the estimated coefficients reveal a convex relationship of our lender distance measure and all coefficient estimates are significant at the 1%-level. Consistent to our findings from syndicate member choice, we find that lead arrangers prefer to allocate higher loan shares in both close syndicates

[19] Note, median (mean) distance between two lenders is 0.63 (0.61), and the centered 80% interval ranges from 0.29 to 0.88. One standard deviation of distance between two lenders is 0.23.

[20] All results continue to hold once we take each individual lenders' loan share as observations for the regressions.

and distant syndicates (compared to mid syndicates). For close and mid syndicates, for example, a smaller lender distance is associated with higher loan shares across all loan roles (see Figure 4.5). This effect is most pronounced for lead arrangers (and co-agents) compared to participants. For example, on average the loan share for lead arrangers of syndicates with a lender distance being one standard deviation smaller than the median syndicate lender distance have a 5.4%-points (or 17% at a mean of 31.4%-points) higher loan share. In contrast, the lower sensitivity of the loan share of participants to variations in syndicate lender distance is consistent to a higher average number of participants in loan syndicates. Overall, these findings are consistent to our results on syndicate structure from Table 4.3 above and show that lead arrangers form more concentrated syndicates by allocating higher loan shares for both close and distant (compared to mid) syndicates.

Analyzing the allocation of loan shares among lenders of the same role within the syndicate also provides consistent results. As shown in Appendix Table A.4.4, lead arrangers allocate higher loan shares to lenders across all loan roles once the distance between the lead arranger and the lender reduces. These effects are all statistically significant, and the economic magnitude is most pronounced for participant lenders. Consequently, lead arrangers also discriminate in the allocation of loans shares among lenders within a syndicate.

When investigating the retained loan share by lead arrangers across loans with different degrees of information asymmetries, we find additional evidence consistent with improved screening and monitoring abilities of close syndicates (hypothesis 1). The literature on information asymmetries in syndicated loans has shown that if informational asymmetries are severe, lead arrangers retain a higher loan shares (e.g., Sufi (2007)). However, if screening and monitoring expertise is indeed higher in close syndicates, lead arrangers might not have to signal credit quality, or mitigate moral hazard by retaining larger loan shares for those loans with higher informational asymmetries. Consistent with this conjecture, we show that lead arrangers do not retain higher loan shares in syndicates with high information asymmetries of borrowers once the syndicate distance is close (see Appendix Table A.4.5). In comparison, for syndicates with mid and distant lender distance, lead arrangers retain higher loan shares. Also, analyses for the concentration of syndicates (Herfindahl) show consistent results.

4.4.3 Close versus Mid versus Distant Syndicates

The above tests provide important insights into how lead arrangers structure loan syndicates, choose syndicate partners, and allocate loan shares. The question of who benefits from these different types of syndicate formation remains to be answered. To address this question, and summarize our results on how syndicate formation differs across syndicated loan lender distance, we analyze how syndicates differ across lender distance.

We use the syndicated loan lender distance (as defined in equation (2)) to group our sample of syndicated loans into terciles, i.e. close, mid, and distant syndicates.[21] The sub-

[21] We choose three groups to reflect the non-linearity of our results above.

sample of close syndicates consist of syndicates, in which lender distance is below the lowest one-third lender distance in the originating month. The sub-sample of mid syndicates are syndicates with lender distance above the lowest one-third and below the lower two-thirds of lender distance in the originating month, whereas distant syndicates consist of the reaming syndicates, i.e. those with lender distance above the lowest two-thirds in the originating month. We then look into differences in borrower characteristics, loan characteristics, syndicate structure, and loan distribution across close, mid, and distant syndicates.

Table 4.6 reports the mean values for these three sub-samples (columns (1) to (3)). Also, in columns (4) to (5) the table reports the mean differences between close and mid syndicates (μ_{Close} - μ_{Mid}), as well as distant and mid syndicates ($\mu_{Distant} - \mu_{Mid}$), which are all statistically significant. We find that on average borrowers in mid syndicates are most likely to be public firms, more likely to be rated (and more likely to be investment-grade rated), have borrowed previously most often from the syndicated loan market (and are least likely to be first time borrowers in the syndicated loan market), and show higher sales at closing. In addition, mid syndicates have on average larger loan sizes, tend to have longer maturities, have fewer term loans, and lower interest spreads on drawn funds over LIBOR. In terms of syndicate formation, mid syndicates have on average the largest number of lenders (also, across all lender roles), lenders hold smaller loan shares (also across all lender roles), and syndicates are consequently least concentrated. In other words, mid syndicates seem to have safer borrowers and safer loans, which is reflected in less concentrated syndicates (compared to close, and distant syndicates). These results are consistent to previous findings that loans with intermediate lender distance form larger and less concentrated syndicates, also because of lower information asymmetries. In contrast, distant syndicates lend on average to riskier borrowers, lend smaller loan amounts, and charge higher interest spreads on drawn funds over LIBOR. Syndicates consist on average of fewer lenders, lenders retain higher loan shares, and loans are more concentrated.

Close syndicates lend on average to somewhat riskier borrowers than mid syndicates (but much safer than distant syndicates), and lend smaller loan amounts with somewhat shorter maturities. Consistent with slightly riskier borrowers, but safer loans than mid syndicates, interest spreads on drawn funds over LIBOR are a bit higher than for mid syndicates. However, syndicate formation differs considerably. Close syndicates consist of on average only five lenders (compared to 9 lenders for mid syndicates), with fewer lenders across all lender roles (leads, co-agents, and participants). Consequently, loan shares are higher across all lender roles, with a lead arranger retaining on average about one-third of the loan (compared to about one-fifth for mid syndicates). Correspondingly, syndicate concentration is highest.

These findings resemble our previous results that lead arrangers form small and concentrated syndicates consisting of lenders with higher similarity in their lending expertise that might enable those lenders to perform improved screening and monitoring (Hypothesis 1), and/or collude on loan pricing (Hypothesis 2). At this stage, it remains unclear who benefits from these close syndicates.

In the following sub-sections, we address this question and investigate the effects of syndicated loan lender distance and market concentration on loan pricing.

4.4.4 Distance and Loan Pricing

As discussed in the theoretical framework, there are potentially two opposing effects on loan pricing from close syndicates with high similarity in lenders lending expertise. On the one hand, borrowers might benefit from improved screening and monitoring, because lead arrangers can pass on some of these savings to borrowers (Hypothesis 1). On the other hand, borrowers might be "locked-in" into close syndicates so that lenders would be more likely to extract rents (Hypothesis 2). We first examine the *net* effect of these two opposing forces by estimating the following regression model

$$Spread_{i,t} = \alpha + \beta_1 \cdot Distance_{i,t} + \beta_2 \cdot Distance^2_{i,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t} \tag{4.5}$$

where the dependent variable $Spread_{i,t}$ is the interest spread over LIBOR on drawn funds of syndicate i originated in month t. The key right-hand-side variables $Distance_{i,t}$ (and $Distance^2_{i,t}$) measure the (squared) syndicated loan lender distance of lenders in syndicate i in the 12 months prior to month t. We allow ex-ante for a non-linear relationship of $Distance_{i,t}$ on loan pricing, because (i) the stand alone effects of closer lender distance might neither linearly reduce loan pricing due to lower production costs of borrower-specific information, nor linearly increase loan pricing due to borrower "hold-up"; and (ii) the net effect might be dominated by either of the two opposing effects across different levels of lender distance. We separately test for whether the *net* effect of lender distance on loan pricing is linearly, or non-linearly. If lender distance reduces loan pricing for closer syndicates, the improved screening and monitoring effect dominates (Hypothesis 1). If lender distance increases loan pricing for closer syndicates, the price collusion effect dominates (Hypothesis 2). In addition, besides analyzing the effect of lender distance on loan pricing across the entire sample period, we also investigate the time-variation of this effect. Specifically, we test whether the effect of lender distance on loan pricing changed after the Global financial crisis (since 2010). The control variables, fixed effects, and standard errors specification is identical to Table 4.3.

Table 4.7 reports the regression results. Columns (1) and (2) report results for the entire sample period, and show that a reduction in lender distance monotonically reduces loan pricing (see Figure 4.6 (a)). In the linear specification, loan lender distance is statistically significant at the 1%-level, while at the non-linear specification only the squared lender distance is statistically significant. In terms of magnitude, a reduction of lender distance by one standard deviation from the median reduces loan pricing by 5bps (or 2.0% at a mean of 252bps) in the linear specification and by 1.5bps (or 0.6%) in the non-linear specification. Consequently, these results provide mixed evidence on the *net* effect of close syndicates on loan pricing. While significant economic reductions in the linear specification is consistent with improved screening and monitoring (Hypothesis 1), the marginal economic effect in the non-linear specification might indicate collusive loan pricing (Hypothesis 2).

The results on the time-variation of lender distance on loan pricing are reported in columns (3) to (6). Lender distance has a positive and linear effect on loan pricing from 1989 to 2009, while the effect is convex from 2010 to 2017 (see Figure 4.6 (b)). These coefficient estimates are all statistically significant at the 1%-level. In terms of magnitude, a reduction of lender distance by one standard deviation from the median reduces loan pricing by 5bps (or 2.0% at a mean of 252bps) until 2009, while *increases* loan pricing by 10bps (or 4%) since 2010. This implies that the effect of close syndicates on loan pricing significantly changed after the Global financial crisis. Consequently, in close syndicates the *net* effect of lender distance on loan pricing is dominated by improved screening and monitoring (Hypothesis 1) until 2009, while it is dominated by collusive pricing (Hypothesis 2) since 2010. At this stage it remains unclear, why loan pricing increased for close syndicates since 2010. To answer this question, we next disentangle the two opposing effects of improved screening/monitoring and price collusion.

4.4.5 Improved Screening versus Price Collusion

To disentangle the opposing effects of improved screening/monitoring and price collusion, we utilize the cross-sectional variation in the degree of informational asymmetries of the borrower. That is, we split borrowers into "opaque" and "non-opaque" firms, with loans to opaque borrowers having a higher degree of information asymmetry. If price collusion is identical across opaque and non-opaque borrowers, the difference between loan pricing for opaque and non-opaque borrowers quantifies a lower bound for the stand alone effect of improved screening/monitoring.[22] Consequently, the stand alone effect of price collusion is bounded above by the overall *net* pricing effect minus the upper bound of the improved screening/monitoring effect. Also, the stand alone effect of price collusion is bounded below by zero.

We disentangle the stand alone effects of improved screening/monitoring and price collusion separately for each of the two sub-periods discussed above. This approach also allows us to investigate the change magnitude of the stand alone effects over time, thus providing insights why loan pricing increased for close syndicates since 2010. We estimate the following regression model

$$
\begin{aligned}
Spread_{i,t} = {} & \alpha + \beta_1 \cdot Distance_{i,t} + \beta_2 \cdot Distance_{i,t}^2 \\
& + \beta_3 \cdot Distance_{i,t} \cdot Opaque_i + \beta_4 \cdot Distance_{i,t}^2 \cdot Opaque_i \\
& + \gamma \cdot X_{i,t} + \varepsilon_{i,t}
\end{aligned}
\tag{4.6}
$$

[22] The difference captures a lower bound, as lenders in closer syndicates might also mitigate some degree of information asymmetry in loans to non-opaque borrowers. Also, if lenders collude more in loan pricing to opaque borrowers than to non-opaque borrowers (e.g., because the hold-up problem of non-opaque borrowers is more severe), our findings would continue to represent a lower bound.

where the variables $Spread_{i,t}$ and (squared) $Distance_{i,t}$ are defined as in the regression model (4.5). For the same reasons as discussed above, we again allow ex-ante for a possible non-linear relationship of $Distance_{i,t}$ on loan pricing. $Opaque_i$ is an indicator variable for whether syndicated loan i is taken by an opaque borrower, with "opaque" borrowers being defined as unrated firms, or small firms.[23] The key right-hand-side variables are the interaction terms of $Distance_{i,t}$ (and $Distance^2_{i,t}$) with $Opaque_i$. That is, whether the effect of lender distance on loan pricing differs for opaque (compared to non-opaque) borrowers. The control variables, fixed effects, and standard error specifications are identical to regression model (4.5) above, besides that we include a base line effect for opaque borrower (instead of unrated borrower).

Table 4.8 presents the estimates. Consistent with Table 4.7, the coefficient estimates reveal a linear relationship between lender distance and loan pricing until 2009 (see columns (1) and (2) and Figure 4.7 (a)). However, the effect is only statistically significant for loans with high informational asymmetries. In terms of magnitude, a reduction of lender distance by one standard deviation reduces loan pricing for opaque borrowers (compared to non-opaque borrowers) by 5bps (or 2% at a mean of 252bps). This is our estimated effect for the lower bound of the improved screening and monitoring effect of close syndicates until 2009. Given our estimates of the *net* effect of close syndicates of 5bps from Table 7, our estimate for the price collusion effect until 2009 is zero. In sum, we find evidence consistent with improved screening and monitoring of close syndicates until 2009 (Hypothesis 1), but no evidence on price collusion (Hypothesis 2).

Columns (3) and (4) report the estimates for the sub-period from 2010 to 2017. Consistent with Table 4.7, the coefficient estimates reveal a non-linear relationship between lender distance and loan pricing since 2010. In terms of statistical significance, the standalone effect of (squared) lender distance and the interaction terms of (squared) lender distance with opaque borrowers are all statistically significant at least at the 5%-level. Despite statistical significance, loan pricing remains unchanged for close syndicates once lender distance reduces (see Figure 4.7 (b)). However, for non-opaque borrowers smaller lender distance *increases* loan pricing for close syndicates (see Figure 4.7 (b)). In terms of magnitude, in loans to non-opaque borrowers a reduction in lender distance by one standard deviation from the median increases loan pricing by 18bps (or7% at a mean of 252bps). This negative *net* effect of loan pricing for loans to non-opaque borrowers is consistent with price collusion in close syndicates (Hypothesis 2). We thus quantify the lower bound for the improved screening and monitoring effect of close syndicates since 2010 as 18bps. Consequently, we find evidence for both improved screening and monitoring (Hypothesis 1) as well as price collusion (Hypothesis 2) in close syndicates since 2010. While the magnitude of the improved screening and monitoring effect increased over time, the opposing price collusion effect increased in higher magnitude dominating the *net* effect of

[23]Small firms are defined as the smallest one-third of borrowing firms in the sample by sales at closing at the time of loan origination. Our results continue to hold if we define "opaque" borrowers solely by unrated borrowers.

loan pricing since 2010. The question of why lenders in syndicates started to collude on loan pricing remains to be answered.

4.4.6 Market Concentration and Loan Pricing

A possible explanation for the occurrence of price collusion since 2010 as show above might be low market concentration. As stated in hypothesis 3, below a certain level of market concentration, price collusion might increase with further reductions in market concentration. While market concentration declined since the early 2000s, only since 2010 did the syndicated loan market reach low levels of market concentration (see Figure 4.2). Next, we first test hypothesis 3 on a stand alone basis, and then test for the joint effect of hypothesis 2 (price collusion in close syndicates) and 3.

To investigate the effect of market concentration on loan pricing, we add a linear and squared term of market concentration as additional explanatory variables to our regression model (4.5) above. Consistent with our theoretical hypothesis 3, we also allow for a non-linear relationship of market concentration on loan pricing to be able to capture increases in loan pricing for reductions of market concentration below a certain level. We measure market concentration in the syndicated loan market by the Herfindahl index in the 12 months prior to the syndicate origination month. The remaining control variables, fixed effects, and standard error specifications remain identical to regression model (4.5) above, besides that we replace year fixed effects by three-year fixed effects to allow for an identification of the market concentration effect.

To investigate the joint effect of close lender distance and market concentration on loan pricing, we interact our (squared) lender distance measure with indicator variables for different levels of market concentration. We estimate the following regression model

$$\begin{aligned} Spread_{i,t} = \alpha &+ \beta_1 \cdot Distance_{i,t} + \beta_2 \cdot Distance_{i,t}^2 \\ &+ \beta_3 \cdot Distance_{i,t} \cdot MarketConcLow + \beta_4 \cdot Distance_{i,t}^2 \cdot MarketConcLow \\ &+ \beta_5 \cdot Distance_{i,t} \cdot MarketConcHigh + \beta_6 \cdot Distance_{i,t}^2 \cdot MarketConcHigh \\ &+ \gamma \cdot X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4.7}$$

where the variables $Spread_{i,t}$ and (squared) $Distance_{i,t}$ are defined as above. $MarketConcLow_t$ and $MarketConcHigh_t$ are indicator variables for whether the market concentration in the 12 months prior to month t is low, or high, respectively (with intermediate market concentration is the omitted group). Specifically, we split market concentration into terciles, with low market concentration being the lowest one-third of observations in our sample period and high market concentration as the highest one-third (and intermediate market concentration the remaining one-third). Splitting market concentration across terciles again might allow us to capture a non-monotonic effect of market concentration on loan pricing as predicted in hypothesis 3. The key independent variables are the interaction terms of $Distance_{i,t}$ (and $Distance_{i,t}^2$) with $MarketConcLow_t$ and

$MarketConcHigh_t$. The remaining control variables, fixed effects, and standard error specifications are identical to the specification for the stand alone effect of market concentration, besides that we additionally include indicator variables for low and high market concentration.

Column (2) in Table 4.9 reports the regression results for the stand alone effect of market concentration. We find a statistically significant and convex relationship of market concentration on loan pricing. Consistent with hypothesis 3, reductions in market concentration first reduce loan pricing, but below a certain level loan pricing increases with further reductions in market concentration (see Figure 4.8 (a)). In terms of magnitude, a reduction of lender distance by one standard deviation from the median *increases* loan pricing by 2bps (or 1% at a mean of 252bps). While small in economic magnitude, this effect might be more pronounced for close syndicates.

Column (3) reports coefficient estimates for the joint test of hypothesis 2 and 3. We find that the interaction terms of (squared) lender distance with low and high market concentration are statistically significant at least at the 5%-level (with intermediate market concentration being the omitted group). Consistent with standard industrial organization intuition that lower market concentration increases competition, a reduction in market concentration from high to intermediate levels reduces loan pricing across all levels of lender distance (see Figure 4.8 (b)). Consistent with collusive pricing in markets with syndication during periods of low market concentration (hypothesis 3), however, once market concentration declines from intermediate to low levels, loan pricing does not continue to reduce across all levels of lender distance. Specifically, while loan pricing further reduces (or remains unchanged) for mid and distant syndicates, consistent with our hypothesis on price collusion in closer syndicates (hypothesis 2) loan pricing *increases* for close syndicates (see Figure 4.8 (c)). In terms of magnitude, a reduction of market concentration from intermediate to low *increases* loan pricing for close syndicates by 8bps (or 3% at a mean of 252bps) at the 25th-percentile of lender distance, and 13bps (or 5%) at the 10th-percentile, respectively. This finding is consistent with the joint effect of hypothesis 2 and 3, namely that during periods of low market concentration only close syndicates engage in collusive loan pricing. This result implies that the *net* pricing effect of close syndicates is dominated by improved screening and monitoring during periods of high and intermediate market concentration, while it is dominated by price collusion during periods of low market concentration.

4.4.7 Robustness

One concern might be that our results on the time-variation of loan pricing are affected by low levels of market concentration since 2010. To rule out this concern, we re-estimate our results on the time-variation of loan pricing restricting the first sub-period to an (equivalently long) period of low market concentration, namely 1989-1996:q1. As reported in Appendix Table A.4.6, this robustness check confirms our previous results. That is, consistent to hypothesis 1, closer lender distance linearly reduces loan pricing prior to 2010. Our findings thus indicate that despite low levels of market concentration, lenders in close syndicates did not collude on loan pricing prior to 2010. Consequently, these findings also imply that price collusion in the syndicate loan market since 2010 might be an active choice of lenders.

4.5 Conclusion

In this paper, we investigate the formation of loan syndicates and their effects on loan pricing. Consistent with our hypotheses of smaller and more concentrated syndicates magnifying close syndicates' improved screening/monitoring and price collusion abilities, we find that lead arrangers form close and concentrated syndicates by choosing lenders with similar lending expertise and allocating these lenders higher loan shares. Analyzing the effects of close syndicates on loan pricing, we find evidence of both improved screening/monitoring abilities and price collusion. However, while close syndicates resulted in improved screening/monitoring throughout the entire sample period, close syndicates only engaged in price collusion since 2010. Analyzing the effects of market concentration on loan pricing shows that below a certain level of market concentration, price collusion increases with reductions in market concentration. Investigating the joint effect of close syndicated and market concentration shows that close syndicates engage in price collusion only during periods of low market concentration. Overall, our findings imply that both the organizational form of loan syndicates and the level of market concentration affects price collusion.

Our empirical findings have two important implications. First, to our knowledge we are the first to provide evidence of price collusion in markets with syndication beyond the well-documented price collusion in IPO markets. We are also the first to show that both the organizational form of loan syndicates and the level of market concentration affects price collusion. Thereby, we provide empirical evidence consistent with the theory of price collusion in syndicate markets from Hatfield et al. (2017), which contradicts standard industrial organization intuitions.

Second, our work also highlights an important channel of how banks become interconnected in the financial system. As discussed above, borrowing volumes from syndicated loans are larger than from public debt and equity issuance combined, so that banks interconnectedness through syndicated loans is relevant. Banks increase their portfolio overlap with close competitors by forming close and concentrated loan syndicates. As shown in Cai et al. (2018), higher interconnectedness of banks through similarity in their syndicated lending elevates systemic risk during recession periods. We document a new channel of how banks become interconnected, namely through the formation of close and concentrated loan syndicates.

4.6 Figures

Figure 4.1: Mean Syndicated Loan Lender Distance Across Time

This figure shows the annual mean lender distance of syndicated loans from 1989 to 2016. Lender distance of the syndicated loan is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization by borrower 2-digit SIC industry.

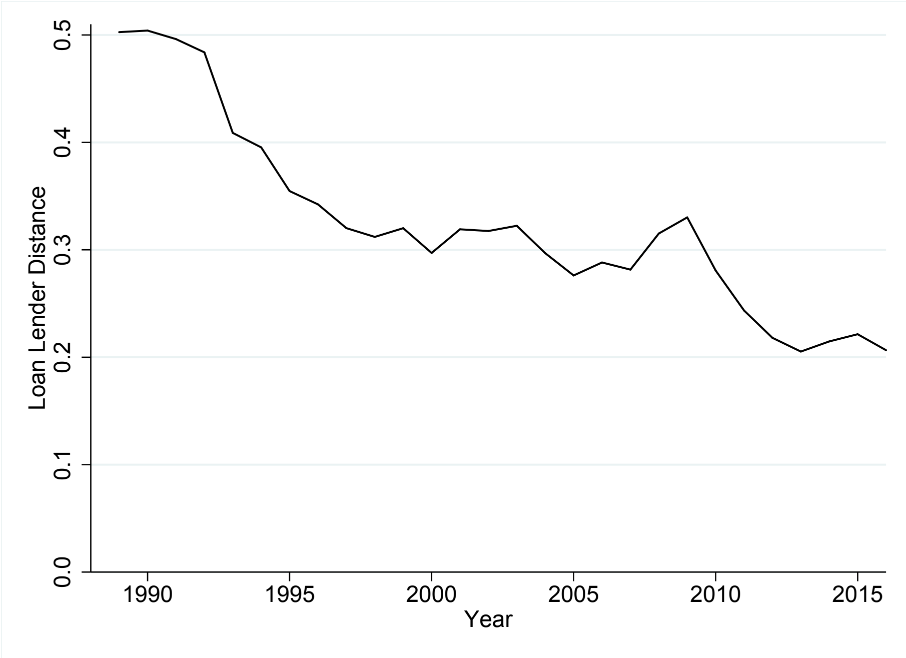
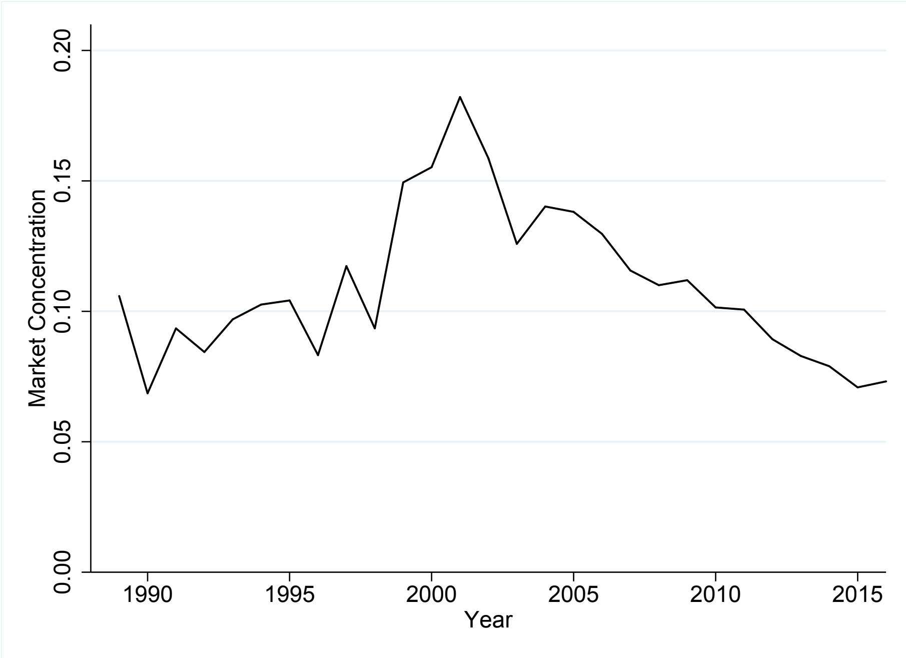


Figure 4.2: Market Concentration of the U.S. Syndicated Loan Market Across Time

This figure shows the market concentration of the U.S. syndicated loan market from 1989 to 2016. Market concentration is the Herfindahl index based on the market share of each bank based on the originated loan amount as lead arranger during the year.



4.7 Tables

Table 4.1: Summary Statistics for Syndicated Loan Facilities

This table presents summary statistics for the sample of syndicated loan facilities made to U.S. firms between January 1989 and March 2017. Panel A reports lead arranger characteristics based on 33,861 unique lead arranger-months. Panels B and C report borrower and loan characteristics, respectively, based on 123,752 loan facilities. Panel D reports market characteristics based on 339 months.

(a) Lead Arranger Characteristics
(Based on 33,861 lead arranger-months, and 3,346,592 lender pair-months)

	N	Mean	SD	10th	50th	90th
Market share (%), previous 12 months	33,861	1.00	3.14	0.00	0.08	1.97
# of loans as lead arranger	33,861	65.05	174.91	1	10	155
$ of loans as lead arranger ($mm)	33,861	11,288	40,244	43	703	21,792
Bank indicator	33,861	0.82	0.39	0	1	1
All lender pairs:						
Distance between two lenders	3,346,592	0.61	0.23	0.29	0.63	0.88

(b) Borrower Characteristics
(Based on 123,752 loan facilities)

	N	Mean	SD	10th	50th	90th
All borrowers:						
Sales at closing ($mm)	69,357	3,541	18,683	59	500	6,881
# of previous syndicated loans	123,752	4.13	6.35	0	2	12
First borrower loan indicator	123,752	0.38	0.49	0	0	1
Private borrower indicator	106,976	0.64	0.48	0	1	1
Public borrower indicator	106,976	0.36	0.48	0	0	1
Borrowers with *Compustat* data:						
Total book assets ($mm)	46,533	12,317	71,769	107	1,158	17,643
Book leverage ratio	46,297	0.37	0.27	0.05	0.34	0.68
Earnings to asset ratio	44,022	0.06	0.24	-0.01	0.07	0.16
Debt rating indicator	48,317	0.56	0.50	0	1	1
Investment-grade rating ind.	48,317	0.29	0.45	0	0	1

Table 4.1: Summary Statistics for Syndicated Loan Facilities (continued)

(c) Loan Characteristics
(Based on 123,752 loan facilities)

	N	Mean	SD	10th	50th	90th
Syndicated loan characteristics:						
Facility amount ($mm)	123,752	271	683	14	95	600
Maturity (months)	112,647	50	25	12	60	80
Spread on drawn funds (bps)	104,950	252	164	63	225	450
Term loan indicator	123,752	0.34	0.47	0	0	1
Purpose of loan indicators:						
Working capital/corporate	123,752	0.72	0.45	0	1	1
Refinancing	123,752	0.18	0.38	0	0	1
Acquisitions	123,752	0.22	0.42	0	0	1
Backup lines	123,752	0.05	0.22	0	0	0
Syndicate structure:						
Total number of lenders	123,752	6.04	6.83	1	4	13
Total number of lead arrangers	123,752	1.55	1.24	1	1	3
Total number of co-agents	123,752	1.30	2.56	0	0	4
Total number of participants	123,752	3.16	5.42	0	1	8
Concentration of syndicate (Herfindahl)	23,194	0.27	0.24	0.06	0.19	0.55
Loan distribution:						
% kept by lead arranger	23,633	31.37	23.94	8.10	24.00	64.00
% held by co-agents	11,679	14.68	10.77	5.18	11.55	28.45
% held by participants	20,847	14.70	13.39	3.23	10.00	33.33
Syndicated loan lender distance:						
Lender distance	100,015	0.29	0.14	0.15	0.26	0.47

(d) Market Characteristics
(Based on 339 months)

	N	Mean	SD	10th	50th	90th
Market concentration	339	0.11	0.03	0.08	0.10	0.15

Table 4.2: Top Lead Arrangers, by Loan Lender Distance

This table shows the top five lead arranger (by number of arranged loans) for close, mid, and distant syndicates in the sample from 2014 to 2016. The sub-sample of close, mid, and distant syndicates consist of syndicates, in which the lender distance is in the lowest, middle, and highest one-third of the originating month, respectively. Lender distance at the syndicated loan facility level is defined as the average distance between the lead arranger(s) and all other syndicate members in the previous 12 months based on lender specialization in borrower 2-digit SIC industry.

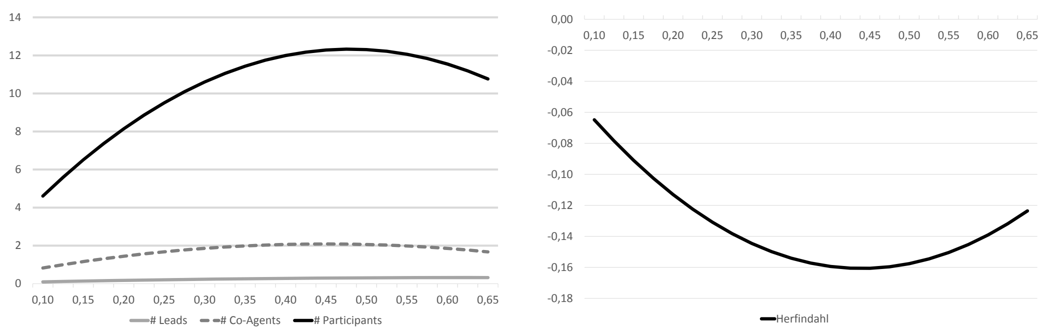
(1) Close Syndicates		(2) Mid Syndicates		(3) Distant Syndicates	
Lead arrangers					
	# loans		# loans		# loans
Bank of America	2,054	Bank of America	827	Bank of America	1,912
JPMorgan Chase	1,794	JPMorgan Chase	667	JPMorgan Chase	1,682
Wells Fargo	1,544	Wells Fargo	490	Wells Fargo	1,327
Citigroup	823	KeyCorporation	476	Citigroup	835
Deutsche Bank	659	Bank of Montreal	389	Barclays	620
Total number of lead arrangers	12,583	Total number of lead arrangers	11,720	Total number of lead arrangers	15,563

Table 4.3: Syndicate Structure

This table reports coefficient estimates from regressions relating syndicate structure to lender distance of the syndicated loan. The dependent variables are the number of lenders, leads, co-agents, and participants in a syndicated loan, and the concentration of the loan syndicate (Herfindahl). Concentration of the loan syndicate is computed as the sum of the squared loan share of each individual syndicate member, and can range between zero and one, with larger values indicating a higher concentration. Lender distance of the syndicated loan is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization by borrower 2-digit SIC industry. All regressions include year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1) # Lenders	(2) # Leads	(3) # Co-Agents	(4) # Participants	(5) Herfindahl
Lender distance	61.902***	1.024**	9.288***	51.455***	-0.732***
	(3.932)	(0.406)	(0.967)	(3.073)	(0.065)
Lender distance^2	-64.948***	-0.813**	-10.330***	-53.687***	0.834***
	(4.404)	(0.405)	(1.052)	(3.418)	(0.075)
Private borrower indicator	0.020	0.069***	-0.163***	0.115	-0.006
	(0.128)	(0.022)	(0.051)	(0.118)	(0.004)
Unrated borrower indicator	-0.324*	-0.123***	0.043	-0.248	0.020***
	(0.189)	(0.025)	(0.065)	(0.162)	(0.005)
Investment-grade borrower ind.	0.567*	-0.093**	0.239**	0.423*	-0.002
	(0.301)	(0.046)	(0.118)	(0.215)	(0.005)
First borrower loan indicator	-0.653***	0.088***	-0.040	-0.703***	0.024***
	(0.133)	(0.011)	(0.043)	(0.139)	(0.005)
Ln[borrower's sales at closing]	1.011***	0.111***	0.246***	0.649***	-0.011***
	(0.083)	(0.016)	(0.037)	(0.065)	(0.002)
Ln[loan facility amount]	2.387***	0.094***	0.831***	1.460***	-0.056***
	(0.113)	(0.014)	(0.042)	(0.080)	(0.003)
Ln[loan maturity in days]	1.019***	0.078***	0.286***	0.655***	-0.028***
	(0.114)	(0.024)	(0.045)	(0.097)	(0.003)
Term loan indicator	0.906***	0.101***	-0.041	0.839***	0.016***
	(0.172)	(0.025)	(0.061)	(0.124)	(0.006)
N =	33,709	33,709	33,709	33,709	12,113
Adjusted R^2	0.3555	0.4352	0.2429	0.2438	0.4151

Figure 4.3: Visualization of Coefficient Estimates from Table 4.3



(a) Lender distance and # Leads, Co-Agents and Participants

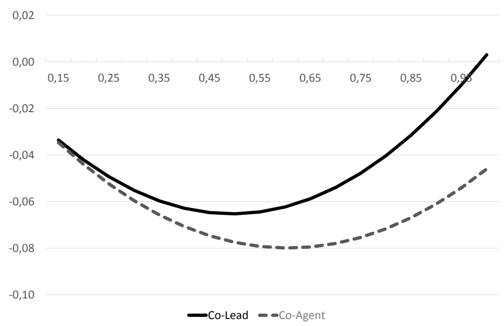
(b) Lender distance and Herfindahl

Table 4.4: Loan Distribution: Choice of Syndicate Members

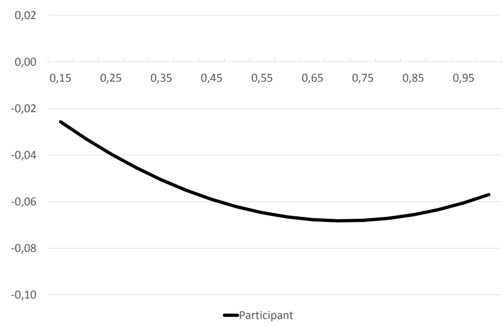
This table reports coefficient estimates from regressions relating the likelihood of a potential lender being chosen as a syndicate member by the lead arranger to the distance between the potential lender and the lead arranger. Lenders can be chosen into different loan roles, namely co-leads, co-agents, or participants. The dependent variable is an indicator variable for whether the potential lender is chosen as a member into these syndicate roles (0 if no and 1 if yes). Chosen co-leads (and co-agents) are excluded from the choice set in subsequent regressions for less senior syndicate membership roles. The independent variable of interest is the distance between the syndicates lead arranger(s) and the potential lender in the previous 12 months based on lender specializations in borrower 2-digit SIC industry. All regressions include loan facility fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1) Syndicate Co-Lead Indicator	(2) Syndicate Co-Agent Indicator	(3) Syndicate Participant Indicator
Distance from lead arranger	-0.264***	-0.264***	-0.192***
	(0.025)	(0.018)	(0.012)
Distance from lead arranger^2	0.267***	0.218***	0.135***
	(0.022)	(0.020)	(0.012)
Previous relationships with lead	-0.001	0.004***	0.014***
	(0.001)	(0.000)	(0.001)
Previous relationships with borrower	0.125***	0.169***	0.246***
	(0.010)	(0.004)	(0.007)
Market share (%), previous 12 months	0.014***	0.005***	0.001***
	(0.001)	(0.001)	(0.000)
Loan facility fixed effects	Yes	Yes	Yes
N =	9,838,197	8,168,392	12,388,715
Adjusted R^2	0.1882	0.1328	0.1612

Figure 4.4: Visualization of Coefficient Estimates from Table 4.4



(a) Distance from Lead Arranger and Syndicate Membership: Co-Lead and Co-Agents



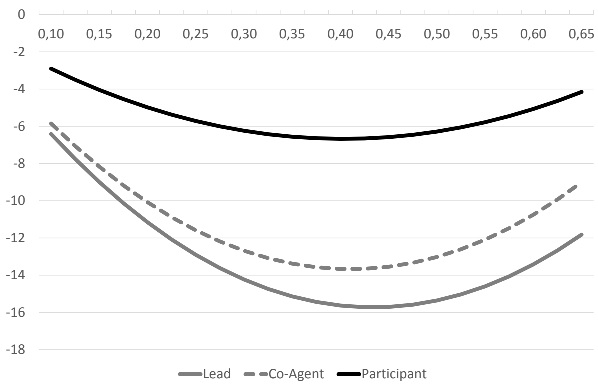
(b) Distance from Lead Arranger and Syndicate Membership: Participants

Table 4.5: Loan Distribution: Allocation of Loan Shares

This table reports coefficient estimates from regressions relating loan distribution to lender distance of the syndicated loan. The dependent variables are the share of the loan in percentage taken by lead arrangers, co-agents, and participants, respectively. Lender distance of the syndicated loan is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization by borrower 2-digit SIC industry. Loan shares are computed as the average loan share of lenders with the same loan role within the syndicate. All regressions include control variables as in Table 4.3 as well as year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1) % Held by Lead	(2) % Held by Co-Agent	(3) % Held by Participant
Lender distance	-72.503***	-66.652***	-33.152***
	(6.922)	(8.090)	(4.725)
Lender distance^2	83.559***	81.215***	41.165***
	(8.371)	(9.163)	(5.423)
Control variables	Yes	Yes	Yes
N =	12,272	7,463	11,474
Adjusted R^2	0.4160	0.4205	0.4886

Figure 4.5: Visualization of Coefficient Estimates from Table 4.5



Lender distance and % held
by Lead, Co-Agent and Participant

Table 4.6: Close vs. Mid vs. Distant Syndicates

This table reports the means of close, mid, and distant syndicates on various borrower, loan characteristics, syndicate structure, and loan distribution, and the mean differences between close and mid as well as distant and mid syndicates. That is, the mean of close syndicates, minus the mean of mid syndicates ($\mu_{Close} - \mu_{Mid}$), and the mean of close syndicates, minus the mean of mid syndicates ($\mu_{Distant} - \mu_{Mid}$), respectively. The sample of 123,752 syndicated loan facilities is split into three sub-samples based on the monthly one-third, and two-thirds of the lender distance of the syndicated loan. The sub-sample of close syndicates consists of syndicates in which lender distance is up to the one-third of the originating month, the sub-sample of mid syndicates consist of syndicates in which lender distance is above the one-third and up to the two-third of the originating month, whereas the sub-sample of distant syndicates consists of the remaining syndicates. Lender distance at the syndicated loan facility level is defined as the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization in borrower 2-digit SIC industry. * indicates that the mean difference is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

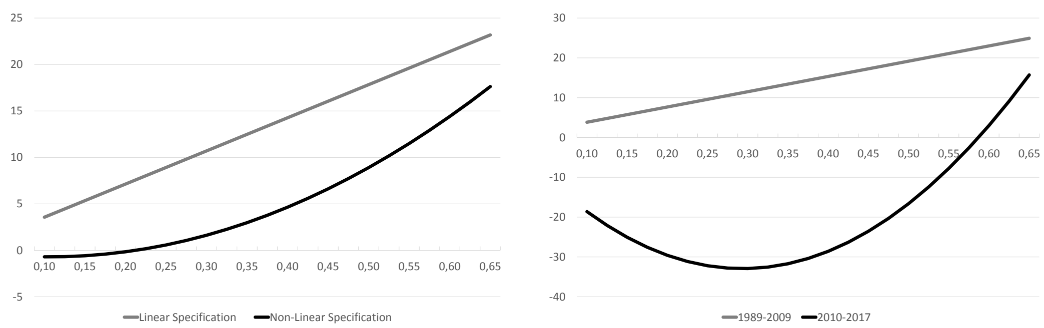
	Syndicate Distance			Differences	
	Close	Mid	Distant	Close-Mid	Distant-Mid
	(1)	(2)	(3)	(4)	(5)
Borrower characteristics:					
Public borrower indicator	0.359	0.406	0.306	-0.047***	-0.100***
Debt rating indicator	0.627	0.667	0.521	-0.041***	-0.146***
Investment-grade rating indicator	0.325	0.373	0.252	-0.048***	-0.121***
# of previous syndicated loans	4.907	5.383	3.502	-0.477***	-1.881***
First borrower loan indicator	0.299	0.281	0.418	0.018***	0.137***
Sales at closing ($mm)	3,893	4,921	3,025	-1,028***	-1,895***
Syndicated loan characteristics:					
Facility amount ($mm)	312	399	221	-87***	-178***
Maturity (months)	48.627	50.940	51.294	-2.314***	0.354*
Term loan indicator	0.322	0.314	0.364	0.008**	0.051***
Spread on drawn funds (bps)	236	231	266	5***	35***
Syndicate structure:					
Total number of lenders	5.202	9.130	6.781	-3.928***	-2.349***
Total number of lead arrangers	1.659	1.821	1.556	-0.162***	-0.264***
Total number of co-agents	1.256	2.149	1.363	-0.892***	-0.786***
Total number of participant lenders	2.273	5.138	3.810	-2.865***	-1.328***
Concentration of syndicate (HHI)	0.270	0.171	0.250	0.098***	0.079***
Loan distribution:					
% kept by lead arranger	31.437	21.316	29.776	10.121***	8.460***
% held by co-agent lender	17.661	12.124	15.531	5.537***	3.407***
% held by participant lender	16.479	10.200	15.578	6.279***	5.378***

Table 4.7: Loan Pricing and Time-Variation in Loan Pricing

This table reports coefficient estimates from regressions relating loan pricing to the lender distance at the syndicated loan facility level, over the entire sample period and a split of the sample period. The sample period is split into a first sub-period from 1989 to 1996:q1, and a second sub-period from 2010 to 2017:q1. The dependent variable is the interest spread over LIBOR on drawn funds measured in basis points. The independent variables of interest is the (squared) lender distance of the syndicated loan, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on borrower 2-digit SIC industry. All regressions include control variables as in Table 4.3 as well as year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Spread on Drawn Funds (bps)					
	Full Sample		1989-2009		2010-2017	
	(1)	(2)	(3)	(4)	(5)	(6)
Lender distance	35.66***	-13.19	38.33***	32.31	-17.94	-224.44***
	(8.56)	(22.75)	(8.82)	(27.93)	(23.32)	(53.04)
Lender distance^2		62.00**		7.44		382.46***
		(29.38)		(34.13)		(82.51)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N =	31,024	31,024	25,774	25,774	5,250	5,250
Adjusted R^2	0.4544	0.4545	0.4578	0.4578	0.4492	0.4509

Figure 4.6: Visualization of Coefficient Estimates from Table 4.7



(a) Lender Distance and Loan Pricing: Full Sample

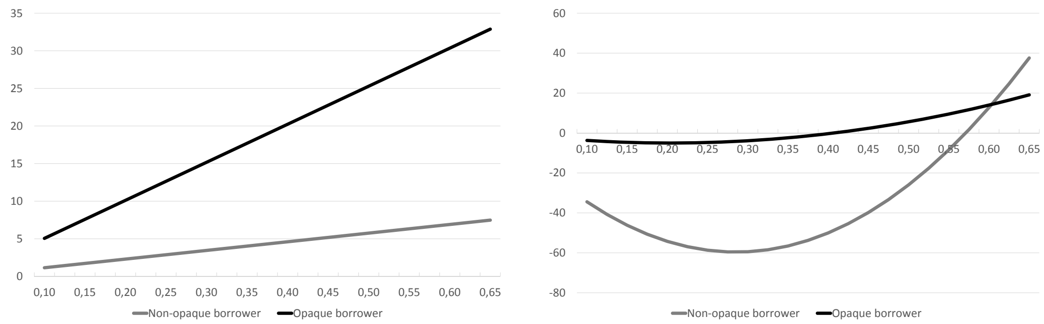
(b) Lender Distance and Loan Pricing: Sub-periods

Table 4.8: Improved Screening versus Price Collusion

This table reports coefficient estimates from regressions relating loan pricing to the lender distance at the syndicated loan facility level and information asymmetry of the borrower, separate for two sub-periods. An "opaque" borrower is an unrated firm, or a small firm (defined as the smallest one-third of borrowing firms in the sample by sales at closing at the time of loan origination). The first sub-period spans from 1989 to 2009, and the second sub-period from 2010 to 2017. The dependent variable is the interest spread over LIBOR on drawn funds measured in basis points. The independent variables of interest are the (squared) lender distance of the syndicated loan, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on borrower 2-digit SIC industry, and interactions of these variables with "opaque" borrower, respectively. All regressions include control variables as in Table 4.3 (besides including an opaque borrower indicator instead of unrated borrower) as well as year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Spread on Drawn Funds (bps)			
	1989-2009		2010-2017	
	(1)	(2)	(3)	(4)
Lender distance	11.51	-5.41	-66.72*	-417.59***
	(12.32)	(38.57)	(39.54)	(124.03)
Lender distance^2		23.47		731.38***
		(47.68)		(216.10)
Lender distance x Opaque	39.07**	100.79*	90.01*	368.37**
	(17.73)	(54.09)	(50.65)	(168.04)
Lender distance^2 x Opaque		-75.94		-610.45**
		(61.26)		(283.09)
Control variables	Yes	Yes	Yes	Yes
N =	25,774	25,774	5,250	5,250
Adjusted R^2	0.4532	0.4532	0.4447	0.4465

Figure 4.7: Visualization of Coefficient Estimates from Table 4.8



(a) Lender Distance and Loan Pricing: 1989 - 2009

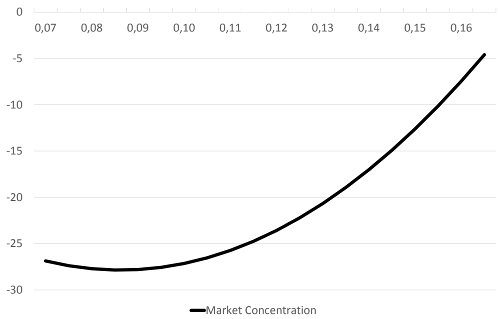
(b) Lender Distance and Loan Pricing: 2010 - 2017

Table 4.9: Loan Pricing and Market Concentration

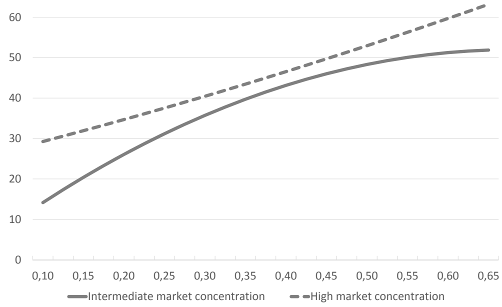
This table reports coefficient estimates from regressions relating loan pricing to the lender distance at the syndicated loan facility level and market concentration. The dependent variable is the interest spread over LIBOR on drawn funds measured in basis points. Market concentration is the Herfindahl index based on the market share of each bank based on the originated loan amount as lead arranger during the previous 12 months. Lender distance of the syndicated loan is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization by borrower 2-digit SIC industry. The independent variables of interest are market concentration (squared) and the interaction of lender distance (squared) with low and high market concentration, whereas low market concentration is an indicator variable for the lowest one-third of market concentration in the sample period, and high market concentration is an indicator variable for the highest one-third of market concentration in the sample period. All regressions include control variables as in Table 4.3 (and column (3) additionally indicators for low and high market concentration) as well as three-year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Spread on Drawn Funds (bps)		
	(1)	(2)	(3)
Lender distance	67.66***	66.60***	152.74***
	(22.99)	(22.66)	(37.64)
Lender distance^2	-14.06	-12.70	-112.22**
	(30.36)	(29.89)	(48.19)
Market concentration		-646.04*	
		(364.09)	
Market concentration^2		3746.33**	
		(1565.41)	
Lender distance x Low market concentration			-170.73***
			(56.01)
Lender distance^2 x Low market concentration			183.74***
			(65.69)
Lender distance x High market concentration			-103.31**
			(48.61)
Lender distance^2 x High market concentration			128.58**
			(58.46)
Control variables	Yes	Yes	Yes
N =	31,024	31,024	31,024
Adjusted R^2	0.4343	0.4354	0.4346

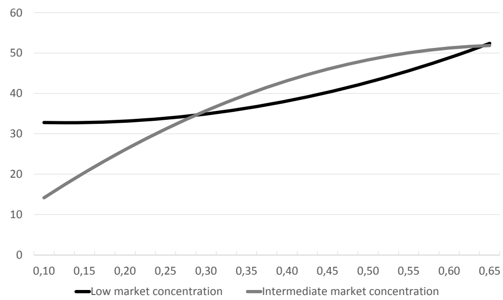
Figure 4.8: Visualization of Coefficient Estimates from Table 4.9



(a) Market Concentration



(b) Lender Distance and Market Concentration: Intermediate vs. High



(c) Lender Distance and Market Concentration: Low vs. Intermediate

4.8 Appendix

Table A.4.1: Variable Definitions

This Appendix lists the variables used in the empirical analysis and their definitions.

Variable	Description
Panel A: Lead Arranger Characteristics	
Market share (%), previous 12 months	Market share of a lender in the U.S. syndicated loan market based on the total loan amount the lender originated during the previous 12 months
# of loans as lead arranger	Number of loans arranged as lead arranger in the U.S. syndicated loan market during the previous 12 months
$ of loans as lead arranger ($mm)	Amount of loans arranged by a lender in the U.S. syndicated loan market in USD million based on the total loan amount the lender originated during the previous 12 months
Bank indicator	An indicator variable for whether the lender is a bank (as opposed to finance companies, institutional investors, etc.)
Lender's previous relationships with lead	An indicator variable for whether a lender previously syndicated a loan with the lead arranger (no matter what roles the two lenders took)
Lender's previous relationships with borrower	An indicator variable for whether a lender previously syndicated a loan to the borrower (no matter what role the lender took)
Distance between two lenders	The distance in lending specializations between two lenders in the U.S. syndicated loan market during the previous 12 months

Variable Definitions (continued)

Panel B: Borrower Characteristics	
All borrowers:	
Sales at closing ($mm)	Borrower's sales at closing in USD million at the time of loan origination
# of previous syndicated loans	The number of syndicated loans that the borrower took prior to the time of loan origination
First borrower loan indicator	An indicator variable for whether the borrower's syndicated loan is the first syndicated loan
Private firm indicator	An indicator variable for whether the borrower is a private firm at the time of loan origination
Public firm indicator	An indicator variable for whether the borrower is a public firm at the time of loan origination
Borrowers with *Compustat* data:	
Total book assets ($mm)	Total assets of a borrower (book value) in USD million at time of loan origination
Book leverage ratio	Book leverage ratio of a borrower at the time of loan origination, computed as $(\textit{Longterm Debt} + \textit{Current Liabilities})/\textit{Total Book Assets}$
Earnings to asset ratio	Earnings to asset ratio of a borrower at the time of loan origination, computed as $(\textit{Depreciation} + \textit{Income before extraordinary items})$ / $\textit{Total Book Assets}$
Debt rating indicator	An indicator variable for whether the borrower has a long-term S&P debt rating at the time of loan origination
Investment-grade rating indicator	An indicator variable for whether the borrower has a long-term S&P investment-grade rating at the time of loan origination
Unrated borrower indicator	An indicator variable for whether the borrower is unrated by S&P (no long-term debt rating) at the time of loan origination
Opaque borrower	An indicator variable for whether the borrower is either an unrated firm or a small firm (defined as the smallest one-third of borrowing firms in the sample by sales at closing at the time of loan origination)

Variable Definitions (continued)

Panel C: Loan Characteristics	
Syndicated loan characteristics:	
Facility amount ($mm)	Facility amount of the syndicated loan in USD million
Maturity (months)	Maturity of the syndicated loan in months
Spread on drawn funds (bps)	Loan interest rate spread over LIBOR on drawn funds measured in basis points
Term loan indicator	An indicator variable for whether the syndicated loan is a term loan
Purpose of loan indicators:	
Working capital/corporate	An indicator variable for whether the purpose of the syndicated loan is either working capital, or corporate
Refinancing	An indicator variable for whether the purpose of the syndicated loan is refinancing
Acquisitions	An indicator variable for whether the purpose of the syndicated loan is aquisitions
Backup lines	An indicator variable for whether the purpose of the syndicated loan is backup lines
Syndicate structure:	
Total number of lenders	Total number of lenders in the syndicate
Total number of lead arrangers	Total number of lead arrangers in the syndicate
Total number of co-agents	Total number of co-agents in the syndicate
Total number of participants	Total number of participants in the syndicate
Concentration of syndicate (Herfindahl)	Syndicate concentration as measured by the Herfindahl index (the sum of squared loan share by individual lenders)
Loan distribution:	
% kept by lead arranger*	Loan share retained by lead arranger(s)
% held by co-agent lender*	Loan share held by co-agent(s)
% held by participant lender*	Loan share held by participant(s)
Syndicated loan lender distance:	
Lender distance	The average distance in lending specializations between the lead arranger(s) and other syndicate members of the syndicated loan in the U.S. syndicated loan market during the previous 12 months
Panel D: Market Characteristics	
Market concentration	Market concentration in the U.S. syndicated loan market as measured by the Herfindahl index (sum of the squared lenders market share during the previous 12 months)

* Represents the average loan share of lead arrangers/co-agents/participants if there is more than one lead arranger/co-agent/participant in the syndicate.

Table A.4.2: Example of Computing the Syndicated Loan Lender Distance

This appendix shows how the syndicated loan lender distance is computed using a real example of a syndicate classified as "close". Specifically, it uses a syndicated loan to Stancorp Financial Group Inc. originated on June 16, 2014 (DealScan facilityid 324171), which displays syndicated loan characteristics similar to the average close syndicate (loan amount: $250 million; loan maturity: 48 months; term loan indicator: zero; spread on drawn funds: 137.5bps). The syndicate also shows a very similar syndicate structure than the average close syndicate in the sample. It consists of five lenders, led by a large lender in the syndicated loan market (Wells Fargo), has two co-agents (JPMorgan Chase, and U.S. Bancorp) and two participants (Barclays, and Goldman Sachs). First, we show the distance between two lenders for each pair of lenders at the loan origination month. Second, we compute the syndicated loan lender distance as the average distance of all pairs of lead arranger-lender at the time of loan origination. Consequently, only the lender distance pairs from Wells Fargo with the other four lenders (JPMorgan Chase, U.S. Bancorp, Barclays, and Goldman Sachs) enter the computation.

Distance between two Lenders

	Wells Fargo (Lead)	JPMorgan Chase (Co-Agent)	U.S. Bancorp (Co-Agent)	Barclays (Participant)	Goldman Sachs (Participant)
Wells Fargo	-				
JPMorgan Chase	**0.097**	-			
U.S. Bancorp	**0.113**	0.103	-		
Barclays	**0.162**	0.104	0.154	-	
Goldman Sachs	**0.151**	0.124	0.132	0.167	-

Computation of Syndicated Loan Lender Distance

$$
\begin{aligned}
Distance_{s,t} &= \frac{1}{N_s}\sum_{n=1}^{N_s} distance_{i^n,k^n,t} \\
&= \frac{1}{4}\left(Distance_{WF,\,JPMC,\,t} + Distance_{WF,\,USB,\,t} + Distance_{WF,\,Barc,\,t} + Distance_{WF,\,GS,\,t}\right) \\
&= \frac{1}{4} \times (0.097 + 0.113 + 0.162 + 0.151) = 0.131
\end{aligned}
$$

Appendix A.4.3: Classification of Lender Roles

We classify lenders into three categories based on the seniority of their role in the syndicate, namely: (i) lead arranger, (ii) co-agent, and (iii) participant lender. Using lender roles from DealScan, we classify a lender as a lead arranger if its "LenderRole" falls into the following: administrative agent, agent, arranger, bookrunner, coordinating arranger, lead arranger, lead bank, lead manager, and mandated arranger. If no lead arranger or multiple lead arrangers are identified, we then cross-check the information with another field named "LeadArrangerCredit". For a lender to be a lead, this field needs to equal "Yes." If two or more lead arrangers are still identified, they are then co-leads.

We identify a lender as a co-agent if it is not in a lead position and its "LenderRole" falls into the following: co-agent, co-arranger, co-lead arranger, co-lead manager, co-lead underwriter, collateral agent, co-manager, co-syndications agent, documentation agent, joint arranger, joint lead manager, managing agent, senior co-arranger, senior co-lead manager, senior co-manager, and syndications agent.

Lenders with neither lead nor co-agent roles are classified as participant lenders.

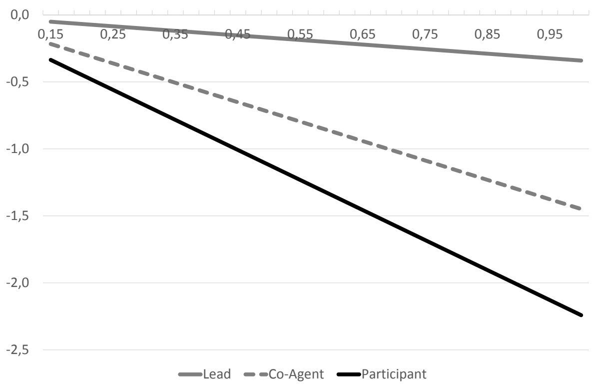
See Standard & Poor's (2016) for descriptions of lender roles.

Table A.4.4: Loan Distribution: Allocation of Loan Shares within Syndicates

This table reports coefficient estimates from regressions relating loan distribution to lender distance of the syndicated loan. The dependent variables are the share of the loan in percentage taken by lead arrangers, co-agents, and participants, respectively. Lender distance of the syndicated loan is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization by borrower 2-digit SIC industry. Loan shares are identified through within syndicate variation and loan shares are lender-specific. Regressions on the loan share for lead arrangers are restricted to loans with at least three lead arrangers. Regressions on the loan share for co-agents and participants are restricted to syndicates with one lead arranger. All regressions include control variables as in Table 4.4 as well as loan facility fixed effects. Robust standard errors allowing for clustering by lead arranger are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1) % Held by Lead	(2) % Held by Co-Agent	(3) % Held by Participant
Distance from lead arranger	-0.341*	-1.449***	-2.241***
	(0.176)	(0.247)	(0.157)
Control variables	Yes	Yes	Yes
Loan facility fixed effects	Yes	Yes	Yes
N =	53,216	25,546	62,918
Adjusted R^2	0.8797	0.9463	0.8963

Figure A.4.1: Visualization of Coefficient Estimates from Table A.4.4



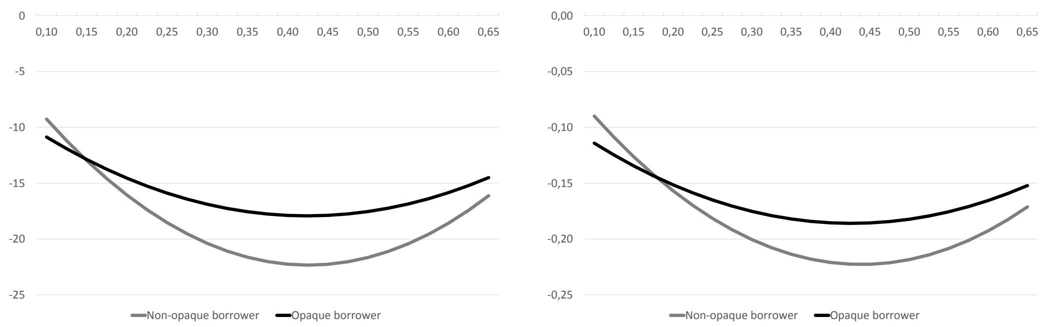
Distance from Lead Arranger and % held by Lead, Co-Agent and Participant

Table A.4.5: Syndicate Formation and Information Asymmetry

This table reports coefficient estimates from regressions relating syndicate formation to lender distance of the syndicated loan and information asymmetry of the borrower. Lender distance of the syndicated loan is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on lender specialization by borrower 2-digit SIC industry. An "opaque" borrower is an unrated firm, or a small firm (defined as the smallest one-third of borrowing firms in the sample by sales at closing at the time of loan origination). A "first" loan is the first syndicated loan the borrower has taken in the syndicated loan market in our sample period. All regressions include control variables as in Table 4.3 (besides including an opaque borrower indicator instead of unrated borrower) as well as year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	% Held by Lead			Herfindahl		
	(1)	(2)	(3)	(4)	(5)	(6)
Lender distance	-72.975***	-104.936***	-82.393***	-0.735***	-1.015***	-0.807***
	(6.978)	(10.963)	(8.005)	(0.066)	(0.104)	(0.071)
Lender distance^2	84.306***	123.289***	95.817***	0.838***	1.156***	0.923***
	(8.428)	(13.852)	(10.269)	(0.076)	(0.134)	(0.087)
Lender distance x Opaque		47.985***			0.440***	
		(14.734)			(0.135)	
Lender distance^2 x Opaque		-56.142***			-0.481***	
		(17.031)			(0.155)	
Lender distance x First loan			35.215***			0.287***
			(11.476)			(0.092)
Lender distance^2 x First loan			-37.967***			-0.299***
			(12.514)			(0.098)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N =	12,272	12,272	12,272	12,113	12,113	12,113
Adjusted R^2	0.4155	0.4170	0.4161	0.4151	0.4166	0.4155

Figure A.4.2: Visualization of Coefficient Estimates from Table A.4.5



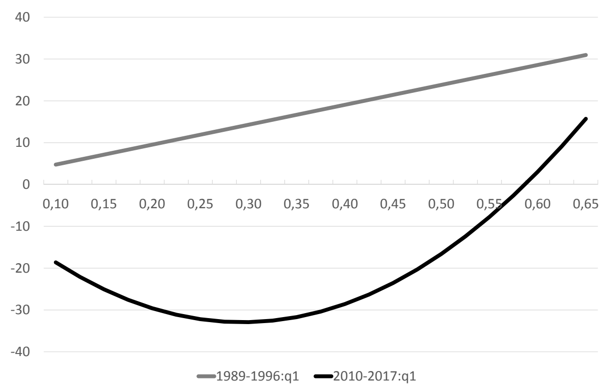
(a) Lender Distance and % held by Lead (b) Lender Distance and Herfindahl

Table A.4.6: Loan Pricing during Periods of Low Market Concentration

This table reports coefficient estimates from regressions relating loan pricing to the lender distance at the syndicated loan facility level, separately across two sub-periods. The sub-period span from 1989 to 1996:q1, and from 2010 to 2017:q1, respectively. The dependent variable is the interest spread over LIBOR on drawn funds measured in basis points. The independent variables of interest is the (squared) lender distance of the syndicated loan, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous 12 months based on borrower 2-digit SIC industry. All regressions include control variables as in Table 4.3 as well as year, loan purpose, interest rate type, borrower 2-digit SIC industry, and borrower state fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Spread on Drawn Funds (bps)			
	1989-1996:q1		2010-2017:q1	
	(1)	(2)	(3)	(4)
Lender distance	47.63***	106.15	-17.94	-224.44***
	(16.78)	(66.92)	(23.32)	(53.04)
Lender distance^2		-59.67		382.46***
		(64.56)		(82.51)
Control variables	Yes	Yes	Yes	Yes
N =	4,872	4,872	5,250	5,250
Adjusted R^2	0.4221	0.4222	0.4492	0.4509

Figure A.4.3: Visualization of Coefficient Estimates from Table A.4.6



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Low Market Concentration

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Frederik Eidam

Diplom-Volkswirt, Master of Science in Finance
Universität Mannheim
Zentrum für Europäische Wirtschaftsforschung
Frankfurt School of Finance and Management

Akademischer Werdegang

10/2002 - 04/2007: Christian-Albrechts-Universität zu Kiel, Diplom-Volkswirt
08/2005 - 05/2006: University of Illinois at Urbana-Champaign, Auslandsstudium
05/2008 - 05/2009: University of Illinois at Urbana-Champaign, M.Sc. Finance
03/2017 - 03/2017: Universität Zürich, Forschungsaufenthalt

Seit 09/2013: Promotion an der Universität Mannheim
Seit 07/2016: Wissenschaftlicher Mitarbeiter am Zentrum für Europäische Wirtschaftsforschung
Seit 09/2017: Wissenschaftlicher Mitarbeiter an der Frankfurt School of Finance and Management

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