Essays on banking and financial innovation

Gong, Di

Publication date:
2015

Document Version
Publisher's PDF, also known as Version of record

Link to publication in Tilburg University Research Portal

Citation for published version (APA):
Gong, D. (2015). *Essays on banking and financial innovation*. CentER, Center for Economic Research.

Essays on Banking and Financial Innovation

Di Gong

November 3, 2015

Essays on Banking and Financial Innovation

Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. E.H.L. Aarts, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Ruth First zaal van de Universiteit op dinsdag 3 november 2015 om 10.15 uur door

DI GONG

geboren op 8 december 1987 te Huainan, Anhui Provincie, China.

Promotiecommissie:

Promotores:	prof. dr. W.B. Wagner
	prof. dr. H.P. Huizinga
Overige Leden:	dr. M.F. Penas
	prof. dr. K.F. Roszbach
	prof. dr. K. Schoors
	prof. dr. I.P.P. van Lelyveld

Acknowledgements

While writing this acknowledgement, I am traveling to Montreal and Vienna. Jet lag, tight conference schedule and deadlines are the key words for this week. Yet I attempt to grasp this opportunity to review of my doctoral study and reflect more broadly my five-year life in the Netherlands using breaks during conference sessions. Precisely five years ago, on the exactly same date, I came to the Netherlands and started my study at Tilburg. Now, it approaches the very end of my doctoral program. Reading through the dissertation, I can see my learning curve. I am certainly a lucky man and would like to express my sincere gratitude to those who helped and supported me over the past years.

First and most, I would like to thank my supervisors, Professor Wolf Wagner and Professor Harry Huizinga, for their enormous help and support.

I am so grateful to Professor Wagner for his wonderful supervision. He became the main supervisor since Jenny passed away. Initially I thought he was fairly strict as he rejected a number of my proposals (which are, low-quality, from a backward view) but did not give any specific research questions to me. Rather, he encouraged me to think independently of the topic for the job market paper. It is honestly an arduous journey until I came up with a reasonable story a couple of months later. Now I am pleased to see this idea having been developed into a full-fledged paper and I sincerely appreciated his persistence on high standard which teaches me the value of perseverance in exploring an uncharted area as a researcher. In addition, I like his liberal way of supervision. He never sets deadlines for me and it seems he always has confidence in my schedule. Besides, sometimes we have lunch meetings where conversations were undertook in a relaxed way. In the serious discussion over various projects, he has excellent intuition and can understand what I would like to do and therefore always make constructive suggestions. Thank you so much, Professor Wagner.

I am indebted to Professor Huizinga for his great guidance. Although I approached Professor Huizinga for supervision in the final year of my PhD, we had intensive meetings over an innovative project about capital arbitrage (which unfortunately is not included in this dissertation). He has amazing insights in the complicated corporate structure and plausible loopholes in the capital regulation, which are extraordinarily impressive to me. At certain point of time, finding some legislation which may invalidate the loophole, I was frustrated and started thinking of the possibility to abandon the project. It is Professor Huizinga who encouraged me to further investigate the changes in regulation until we finally found supportive evidence after reading hundreds of pages of documents. I am grateful to the collaboration with Professor Huizinga on this project and his help in doing empirical work.

I would like to thank my committee members, Dr. Mara Fabiana Pena, Professor Kasper Roszbach, Dr. Iman van Lelyveld, Professor Koen Schoors, for their valuable comments that enabled this dissertation to be in a better shape.

I am indebted to my coauthors, Ata, Kebin, Luc and Thorsten for our collaboration over our joint projects, though some of which are not included in this dissertation. Ata and I had excellent division of labor. Hope we can have even fruitful, productive output in the follow-up project. Kebin and I have met in various conferences at differently locations: Arlington, Lisbon, London, Palma De Mallorca, Amsterdam, Reykjavik, and Vienna. I am grateful to you for introducing me to the Barcelona banking summer school and continuous support in banking research.

I feel like EBC is a big family and enjoy every meeting in junior follow workshops and the Financial Stability Conference. Special thanks to Louis and Carina for the organization of events. Comments from the audience, especially from Burak, Fabiana, Fabio, Olivier, Bernadus, Larissa, Liping, and Yiyi substantially improve my papers. During the three-year doctoral study, I served as teaching assistants for Martin Salm, Harald Benink, Manuel Oechslin and Burak Uras. Thanks for their collaboration. I am grateful to Henk van Gemert for the allocation of teaching task, who always respects

TAs' preference. I am grateful to the staff from CentER, HR, ICT and TiSEM: Ank, Corine, Ella, Kelly, Korine, Mirjam, Nicole, and Sandra. Sincere thanks to your support, which makes every trip pleasant and my work at Tilburg in a good order.

On top of the PhD program at Tilburg, I had great experiences in three high-quality professional training in banking. I am grateful to Xavier Fraxeis and Jose-Luis Peydro for the Barcelona banking summer school, Rafael Repullo for the CEMFI summer school (sponsored by the Erasmus program by the European Commission), and Dirk Shoemaker for the Duisenberg macroprudential regulation course. Furthermore, I feel grateful to the hospitality of the Systemic Risk Centre at the London School of Economics, especially to Jean-Pierre Zigrand for hosting my visit there.

Special thanks go to my three office mates in three years. During my first year of PhD, I shared an office with Hugo in the middle of the corridor. Hugo is a great philosopher from whom I learned Dutch culture, and more importantly, a spiritual way of living. He reminds me the value of peace in our inner world. As Consuelo graduated and left, I moved to the eastern wing and shared the office with Balint in the second year. He is a good colleague who helps me from research experience to useful tips in Stata and Latex. Besides, we shared information on good restaurants and excellent work in photography. In the final year as Balint moved to World Bank, I moved to the wester wing and met Anderson. Although I was busy for conferences and job market, we had lunches together and shared the joys and pressure in the job market.

Thanks to the Utrecht-Amsterdam group of daily commuters: Anton, Ning, Cansu, and Maria Jose. With you guys, the trips were never boring. I thank the Chinese community in Tilburg which are crucial pillars for my stay in Tilburg, especially for the difficult periods of research master. I had great time with RUC alumni in the Netherlands, Xu, Tong and Ning. Moreover, I thank my friends, Shiyang, Cheng, and Tianyu during my stay in London. Besides, I am indebted to Yue from Minnesota and Kristoffer from SSE for the exchange of research ideas.

Memory for Jenny Ligthart lasts forever. She was always enthusiastic and tirelessly available to her students, anytime and anywhere. I remember her as a helpful supervisor and a close friend.

My spiritual pillar also comes from my family. I am immensely grateful to my parents who essentially wished to have me, the only child of the family, physically closer to them, yet showed their enormous tolerance and support to my pursuit of academic research. You are great parents. Same love and gratitude apply to my girlfriend, Shiwei, as well. We met each other in Utrecht when taking the NAKE course together. The great time we had in Utrecht is a life-long treasure to us. We like the Dom, canal and our nice apartment. Let this dissertation lead me to the graduation and start a new chapter of our life in Beijing, with my deepest love and gratitude to you.

Di Gong

18 August 2015

Montreal, Vienna and Tilburg

Contents

List of Figures

Chapter 1

Introduction

Over the past two decades the banking sector experienced drastic changes in both business models and regulation. Securitization as one of the key financial innovations has reformulated banks' balance sheets and led to a new, so-called "originate-to-distribute" model. It is no longer necessary for banks to hold loans to mature on balance sheet. Therefore, banks are more capable of liquidity management and risk sharing. On the other hand, it challenged the traditional regulation as the collapse of the securitization markets was at the center of the recent financial crisis in 2007–2009. Accordingly, Chapters 2 and 3 examine the ex-ante motivation and the ex-post impact of securitization. Departing from the traditional literature of bank-specific drivers for securitization, I investigate the tax incentive for securitization in a cross country setting. In addition, unlike the prior micro studies of the impacts of securitization, for instance, the adverse selection in the securitization market and so forth, I study the macro impact of securitization on real economy. Another strand of my research focuses on banking regulation, especially macroprudential regulation. I am particularly interested in the fact that banks may ex-ante take risk in anticipation of regulatory forbearance in a systemic banking crisis and its implication for macroprudential regulation. Consequently, chapter 4 analyzes systemic risk-taking at banks in the presence of "too-many-to-fail" bailout guarantee. In sum, shedding light on securitization and systemic risk-taking in the banking sector, this dissertation contributes to the policy debate on bank regulation. Each chapter is summarized as follows.

Chapter 2 investigates the tax incentive for securitization. Corporate income taxation, by affecting the after-tax cost of funding, has implications for a bank's incentive to securitize. Using a sample of OECD banks over the period 1999–2006, we find that corporate income taxation led to more securitization at banks that are constrained in funding markets, while it did not affect securitization at unconstrained banks. This is consistent with prior theories suggesting that the tax effects of securitization depend on the extent to which banks face funding constraints. Our results suggest that current corporate income tax systems have distorting effects on banks' securitization decisions.

Chapter 3 analyzes the relationship between country-level securitization and economic activity using an international panel. Our findings suggest that securitization is negatively related to various proxies of economic activity even prior to the crisis of 2007-2009. We explain this finding by securitization spurring consumption at the expense of investment and capital formation. Consistent with this, we find that securitization of household loans is negatively associated with economic activity, whereas business securitization displays a weak positive association with it, and that household securitization increases an economy's consumption-investment ratio. Our results inform recent initiatives aiming at reviving securitization markets, as they indicate that the impact of securitization crucially depends on the underlying collateral.

Chapter 4 empirically studies systemic risk taking by banks. Public guarantees in the event of joint bank failures can result in systemic risk-taking and distort financing decisions of banks. We argue that the pricing of syndicated loans provides an ideal laboratory to study such distortions. In the absence of systemic risk-taking, non-diversifiability of aggregate risk implies that the compensation required for taking on aggregate risk is higher than for idiosyncratic risk. However, in the presence of public guarantees, banks have higher benefits from taking on aggregate risk as this leads to higher correlation across banks. Consistent with the latter, we find that banks charge lower lending interest rates for aggregate risk than for idiosyncratic risk, controlling for firm, loan and bank specific factors. Importantly, there is no evidence for systemic risk-taking for the sample of non-bank lenders who do not benefit from public guarantees. We also find that effect is larger for smaller and less correlated banks, consistent with higher a priori benefits from systemic risk-taking for such banks. The evidence provided suggests that public bail-out policies have significant ex-ante costs by distorting financing decisions in the economy.

Chapter 2

Does Corporate Income Taxation Affect Securitization? Evidence from OECD Banks

2.1. Introduction

Securitization markets have grown rapidly since the 1990s. Before the outbreak of the recent financial crisis, securitization had been seen as a blessing to the banking industry as it provides extra liquidity and improves risk sharing. The dark side of securitization, for instance misaligned incentive problems and increased systemic risk, however, has gradually dominated the debate of securitization and financial turmoil[1]. One central question arises: Why do banks securitize assets extensively? Although much attention has already been paid to banks' business models, the role of taxes is often neglected. In fact, taxation has been considered as a crucial factor in securitization transactions from the perspective of practitioners[2]. Therefore, in this paper we seek to test the effect of corporate income taxes (henceforth, CIT) on banks' incentive to securitize assets.

In a typical securitization transaction, an originator (usually a bank) transfers assets to a special purpose vehicle (henceforth, SPV), which issues asset-backed securities (henceforth, ABS) to investors (Gorton and Souleles 2007)[3]. How does corporate income

[1]Decreased incentives for monitoring and excessive securitization contributed to the increase of systemic risk and eventually the subprime crisis. Nijskens and Wagner (2011) find evidence that banks issuing credit default swaps (CDSs) and collateralized loan obligations (CLOs) pose greater systemic risk.

[2]For example, even though the Indian securitization market grew 15% in the fiscal year 2012, a pending amendment which made the tax status of pass-through entities uncertain hit the market. "Due to lack of clarity on tax incidence on pass-through vehicles, the securitization business has come to a virtual standstill," said Vimal Bhandari, CEO of Indostar Capital Finance. See "Tax issue hits securitization market hard" in Indian Express.

[3]In this paper, the definition of securitization is restricted to the off-balance sheet activity of issuing ABS. This definition is much narrower than the general concept which includes selling loans, issuing standby letters of credit and loan commitments.

tax matter in the securitization process? In principle, a bank can finance on-balance sheet through debt and equity or off-balance sheet through securitization. As corporate income taxes are levied on corporate profits and equity payments are not tax deductible, a higher tax rate raises the tax-adjusted cost of equity. By contrast, the cost of off-balance sheet financing through securitization is assumed to be independent of corporate income taxes. This is because SPVs are usually structured as tax exempt, which serves to ensure as far as possible that no extra tax liability arises from securitization transactions. Overall, corporate income taxes affect funding allocation between on and off-balance sheet. In particular, a higher tax rate increases the tax-adjusted cost of equity and indirectly favors securitization financing. Han et al. (2014) show that this mechanism works for a bank that has substantial loan origination opportunities and limited deposit market power. Specifically, corporate income taxes create an incentive for such "loan-rich, deposit-poor" banks to securitize loans off their balance sheets. Their model also shows that, by contrast, a bank that has limited lending opportunities and plentiful deposit capacities does not respond to taxes. In addition, the authors document empirical evidence from mortgage sales by small banks using variations in U.S. state level corporate tax rates.

Based on the theoretical framework in Han et al. (2014), we extend the analysis to a multi-country setting by examining the tax incentives for the engagement of OECD banks in ABS markets from 1999 to 2006. To identify different responses of funding constrained and unconstrained banks to corporate income taxes, we construct a funding constraint dummy based on banks' loan to deposit ratios. A bank is defined as funding constrained if it has a relatively high loan to deposit ratio. The rationale is that if a bank has abundant loan origination opportunities to fund but is restricted by its limited funding capacities in deposit markets, its funding costs will reflect a cost of deposits at least equal to competitive interest rates. In addition, due to capital requirements, it will have to fund a portion of its loans with an even higher corporate-tax adjusted cost of equity. This weighted competitive cost of deposit funding plus tax-adjusted equity funding can make on-balance sheet financing more expensive relative to securitization. A pool of loans in a corporate-tax exempt securitization vehicle can be funded with competitive financing but without a higher corporate tax-adjusted cost of equity. The relative advantage of securitization grows when the corporate tax rate and equity capital requirement of on-balance sheet funding are higher. Next, taking advantage of cross-country tax variations, we test whether funding constrained banks with headquarters in jurisdictions of high tax rates are inclined to issue more ABS.

Our empirical findings suggest that corporate income taxation led to more securitization at banks constrained at funding markets, while it did not affect securitization at unconstrained banks, in line with the predictions of prior theories. A one standard deviation rise in corporate income tax rates increases the securitization intensity by 1.4%. Therefore, our findings of tax distorting effects are economically important especially when we take into account the large volume of securitization. Our results continue to hold in a battery of robustness checks, which include sample split, alternative dependent variables, a restricted sample excluding U.S. banks, alternative measures of funding constraints, using statutory tax rates and adopting weighted tax rates for multinational banks.

Prior studies suggest that the likelihood and intensity of securitization are largely determined by bank characteristics, such as funding needs (Carlstrom and Samolyk 1995; Demsetz 2000; Loutskina and Strahan 2009; Loutskina 2011), risk exposure (Greenbaum and Thakor 1987; Pavel and Phillis 1987; Panetta and Pozzolo 2010), capital adequacy (Calomiris and Mason 2004; Ambrose et al. 2005; Bannier and Hänsel 2008) and profit opportunities (Affinito and Tagliaferri 2010; Cardone-Riportella et al. 2010). Our paper adds to the literature by providing empirical evidence of tax distorting effects on banks' incentive to securitize assets. This study also contributes to the research at the intersection of taxation and banking that primarily focuses on distorting effects of corporate income taxation on leverages, locations and legal structures of banks (Huizinga 2004), and pass-through of tax burdens (Demirgüç-Kunt and Huizinga 1999, 2001; Albertazzi and Gambacorta 2010; Huizinga et al. 2014).

Unlike Han et al. (2014) using U.S. state level tax variations, we provide empirical evidence of tax distorting effects on ABS issuance by exploiting tax variations across OECD countries. Our cross-country setting has following advantages. First, there are considerable variations in corporate income tax rates across different national jurisdictions[4]. Second, we show the generality of tax distorting effects in heterogenous securitization markets that differ in market size, participation and regulation. However,

[4]Despite a general declining trend, corporate income tax rates remain substantially different across countries. For instance, Ireland and Turkey have effective marginal CIT rates below 10%, whereas Germany and Japan have rates above 35%.

the cross country setting also challenges our identification. To control for country level heterogeneity, we use a series of macroeconomic and regulatory variables. Besides, we construct weighted tax rates based on operating income and profits of foreign subsidiaries for banks operating in multiple jurisdictions. In the end, all results support our predictions and are robust.

The remainder of this paper is organized as follows. Section 2.2 reviews a simplified framework for our analysis and derives testable hypotheses. Section 2.3 presents data sources. Section 2.4 sets out estimation strategies and summary statistics. Section 2.5 contains our empirical analysis and robustness checks. Section 2.6 concludes the paper and proposes policy implications.

2.2. Theoretical Framework

Based on the partial equilibrium models in Pennacchi (1988), Gorton and Pennacchi (1995) and Han et al. (2014), we review a framework to illustrates the tax distorting effects on securitization at banks and derive testable hypotheses.

A bank can invest in loans and money market securities. A loan yields a return r_L when the bank implements screening and monitoring services. At the same time, the bank incurs the cost of providing such services, c. By contrast, investments in money market securities pay an interest rate r_d, equivalent to the cost of wholesale deposit financing. In the end, profits of the bank from all investments are subject to a CIT rate τ.

The bank can finance on-balance sheet through equity and deposits. First, the cost of equity is r_e. Second, the bank may collect retail deposits in the local market at the cost r_D. Han et al. (2014) assume imperfect competition in the retail deposit market by an increasing marginal cost of retail deposits, $\frac{\partial r_D}{\partial D} > 0$. $r_D \geq r_d$ holds for a sufficiently high level of deposits.

Assume two types of banks differ in funding constraints. Funding unconstrained banks have market power in retail deposit markets but no advantage at loan origination. Therefore, the unconstrained banks raise funds at a low cost, equivalent to the cost of wholesale deposits

$$\bar{r}_{onBS} = r_d \tag{2.1}$$

where $\bar{r}_{onBS}$ is the marginal cost of on-balance sheet financing of the funding unconstrained banks and r_d is the cost of wholesale deposits funding. Due to limited loan origination opportunities, the unconstrained banks invest excessive deposits into money market securities. By contrast, funding constrained banks lack deposit market power but have lots of lending opportunities. Funding asset expansion primarily by equity financing, the constrained banks issue retail deposits up to the point where the cost of retail deposit and the tax-adjusted cost of equity are equalized at a point greater than the cost of wholesale deposits in equilibrium

$$\widetilde{r}_{onBS} = \frac{r_e}{1-\tau} = r_D > r_d \tag{2.2}$$

where $\widetilde{r}_{onBS}$ is the marginal cost of on-balance sheet financing of the funding constrained banks. Essentially, the constrained banks find funding loans profitable and invest no money market securities.

Han et al. (2014) assume that a bank can securitize a part of its loans in exchange for additional funding at the cost of $r_{offBS} = r_d$. This is because competitively priced ABS and money market securities can be treated as substitutes when these financial products share similar characteristics of liquidity and risk. Moreover, the cost of funding through securitization is exempt from corporate income taxes because the SPV is structured as an investment vehicle similar to a mutual fund[5]. When securitizing loans, the bank may benefit from a fall in the cost of financing $r_{onBS} - r_{offBS}$, depending on the funding constraint and the cost of on-balance sheet financing. In this way, securitization acts as an off-balance sheet substitute for the conventional on-balance sheet financing.

However, a moral hazard problem arises, limiting the extent to which a bank securitizes loans. Whenever some risk is transferred in securitization, the incentive for banks to

[5]In practice, tax neutrality is usually accomplished in a variety of ways. First, offshore SPVs are widely used to maintain no taxable presence in originator's jurisdiction. Set up in tax havens or tax-friendly countries to OECD, such as Cayman Islands, Irish docks and Jersey, SPVs have access to tax avoidance strategies unpermitted at home jurisdictions. Second, SPVs are structured as tax transparent pass-through entities. For instance, treated as tax transparent and pass-through, real estate mortgage investment conduits (REMICs) are generally not taxed in the U.S. Third, SPVs can be designed to have little material income tax liability, i.e., its deductible expenses perfectly offset income, reducing taxable income to zero.

screen and monitor remains suboptimally low in spite of certain features in securitization contracts targeted at remedying the moral hazard problem[6]. Rational investors of ABS may expect declined screening and monitoring services and therefore discount the value of the loans by a discount factor η. Hence, suffering a loss of the loan value, the bank earns $\eta r_L - F$ in securitization instead of $r_L - c$ when holding loans on the balance sheet until maturity, where F is the fixed cost of securitization[7].

Based on the trade-off between savings of funding costs $r_{onBS} - r_{offBS}$ and losses in loan values $(1-\eta)r_L + F - c$, a securitization project is profitable only if the following condition holds:

$$(r_{onBS} - r_{offBS}) - [(1-\eta)r_L + F - c] > 0 \tag{2.3}$$

Funding unconstrained banks cannot satisfy the condition (2.3) because their marginal cost of on-balance sheet financing is already sufficiently low.

$$(\bar{r}_{onBS} - r_{offBS}) - [(1-\eta)r_L + F - c] = (r_d - r_d) - [(1-\eta)r_L + F - c] < 0 \tag{2.4}$$

Therefore the unconstrained banks merely incur losses in securitization without effectively lowering costs of funding[8]. By contrast, funding constrained banks are likely to benefit from lower funding costs from securitization.

$$(\widetilde{r}_{onBS} - r_{offBS}) - [(1-\eta)r_L + F - c] = (\frac{r_e}{1-\tau} - r_d) - [(1-\eta)r_L + F - c] \gtreqless 0 \tag{2.5}$$

the first term in condition (2.5) is positive because $r_e > r_d(1-\tau)$ always holds, reflecting a tax advantage of debt financing to equity financing[9]. If the tax-adjusted cost of equity is sufficiently large, or the loss of loan values and fixed costs of securitization are sufficiently small, it is possible for the bank to make profits in securitizing loans. Here, corporate

[6] Certain contract features, such as offering implicit recourse, holding equity tranche and over-collateralization, are designed to alleviate the moral hazard problem and to reduce the agency cost of securitization. Consistent with theoretical predictions of reduced incentives to carefully screen and monitor borrowers, some empirical studies find a decline in the credit quality in securitized loans (Keys et al. 2010; Purnanandam 2011; Keys et al. 2012).

[7] Fixed costs usually include the costs associated with setting up SPVs, rating fees, auditing and legal expenses.

[8] Gijle et al. (2013) find that banks experiencing deposits windfalls in U.S. shale-boom counties tend to fund their mortgage lending through low cost deposits instead of securitization.

[9] In Han et al. (2015), when the differences in personal income taxation of debt and equity has been taken into account, although the competitive state prices of equity and debt claims may differ, a net tax advantage to debt financing remains. This analysis is orthogonal to our analysis of tax advantage of securitization financing due to corporate income taxation.

income taxation plays a role. Notably, banks in a jurisdiction of higher tax rates have a higher tax-adjusted cost of equity and thus a higher cost of the on-balance sheet financing. The likelihood of securitization rises in the difference between on-balance sheet financing and securitization financing. Moreover, given that a bank is determined to securitize assets, a higher tax rate that augments the marginal benefit of securitization is expected to increase the volume of securitization.

This framework identifies a micro channel that connects corporate income taxation and bank securitization, depending on bank funding constraints. We derive the following hypotheses:

Hypothesis 1: *Funding constrained banks, namely, banks with plentiful loan origination opportunities but limited deposit capacities, are more likely to securitize and securitize more assets when subject to a higher corporate income tax rate..*

Hypothesis 2: *Funding unconstrained banks, namely, banks with little loan origination opportunities and substantial deposit capacities, have no tax incentive to securitize assets.*

2.3. Data

The data for this research are collected from a number of sources, including ABS Alert, Bankscope, World Development Indicators (WDI), Global Financial Development Database (GFDD), Bank Regulation and Supervision Surveys and Databases.

We use the ABS Alert to identify banks that issued asset backed securities. The ABS Alert is a comprehensive database that presents all rated asset-backed issues placed anywhere in the world since 1985. We drop non-banks sponsors such as airlines, retailers, hedge funds, auto manufacturers and so forth. In addition, we rely on the amount and the pricing date of issuance to determine the intensity and the year of securitization, respectively. For the sake of matching originators in the ABS Alert with banks in Bankscope, we also collect relevant information about seller types, countries of denomination and collateral, currencies and rating agencies. Our analysis of securitization covers the booming period of securitization markets in 1999–2006 for two reasons. On the one hand, some countries lacked legislation that simplifies and encourages the use of securitization as a financing technique before the late 1990s. Therefore, the securitization markets were quite small outside the U.S. before the beginning of our sample period[10]. On the other hand, we exclude the period of the subprime crisis in which securitization transactions were likely to be market driven.

We obtain balance sheets and income statements for financial institutions from Bankscope. Our bank sample consists of bank holding companies, commercial banks, cooperative banks and savings banks with headquarters in 19 OECD countries. Even though finance companies, investment banks, real estate and mortgage banks, specialized governmental credit institution, such as Nissan, Lehman Brothers, Delta Funding and WestLB AG, are important sponsors in ABS markets, we exclude them from our sample as their business models differ substantially from our theoretical analysis. Specifically, these financial institutions are not deposit-taking and loan-making banks. Next, we include banks only if the average of their total assets over the sample period ranks in the upper quartile in the distribution of bank size in each country. We restrict our sample to large banks for two reasons. First, in practice ABS markets are dominated by large banks which usually own the know-how of securitization techniques, good reputation and access to securitization markets. Moreover, large banks are able to undertake the substantial fixed costs in securitization transactions[11]. Second, securitization transactions of large banks contribute to systemic risk and financial fragility. Therefore the ABS issuance of large banks is policy relevant to regulators.

To link the securitization information to bank specific variables, we match originators in the ABS Alert with banks in Bankscope, if they share the identical name and country of residence. We double check the matching process by manually referring to Moody's rating reports for each ABS issuance if rated by Moody, which presents information about all participants involved in the securitization transactions. Our final sample ends up with 4423 banks with headquarters in 19 OECD countries in the 1999–2006 period, in which 265 banks had at least one asset backed issue[12]. Our unit of analysis is the

[10]For instance, the Italian market of securitization had not started growing remarkably until the enactment of Law 130 in 1999.

[11]In practice, small banks with no direct access to ABS markets might sell loans to large institutions that pool and securitize them. This means in some cases the underlying assets of ABS are not originated by the sponsor of ABS, which may bring noises and biases to our analysis. Fortunately, this usually happens in the deals in which large investment banks act as sponsors and are excluded from our sample. Therefore, most securitizing banks in our sample originate loans as the underlying assets and complete off-balance sheet securitization themselves.

[12]Using bank names and countries of residence as a reference, Panetta and Pozzolo (2010) match originators of securitization in Dealogic with banks in Bankscope in a similar study of motivations

bank-year observation.

In our empirical analysis, we implicitly assume that SPVs are corporate tax advantaged relative to banks, because SPVs hold loans funded with debt and equity but are corporate income tax exempt in contrast to banks which hold loans funded with debt and equity and pay corporate income taxes[13]. This is a reasonable assumption as failures of SPVs to be tax exempt would lead to double taxation at both originator and SPV levels, therefore making securitization transactions unprofitable (Gorton and Souleles 2007)[14]. In most specifications, we use effective marginal tax rates of CIT, based on statutory tax rates from the OECD tax database. In one robustness check, we also use statutory tax rates directly.

We use macroeconomic variables from World Development Indicators (WDI) to control for economic growth, inflation and financial development. Additionally, we collect information regarding banking competition from the Global Financial Development Database (GFDD). Moreover, we control for different regulatory and supervisory institutions across countries, based on two rounds of surveys conducted by World Bank (2003 and 2007). The Bank Regulation and Supervision Surveys and Databases cover various aspects of banking and permit the identification of the existing regulation and supervision of banks (Barth et al. 2001).

When calculating profit-weighted and income-weighted tax rates for multinational banks in some robustness checks, we rely on the Bankscope to determine the relationship between domestic parent companies and foreign subsidiaries. Foreign subsidiaries are defined as subsidiaries that are located in another country and are owned by an ultimate home parent company or not ultimately owned but owned at least 51% by the home parent company. Besides, we restrict foreign subsidiaries as those operating in our sample OECD countries. Overall, successfully matched with the parent banks in the Bankscope, 189 banks in our sample are classified as multinational banks having foreign subsidiaries. Last, Appendix Table A.1 provides detailed information for variable definitions and data

for bank securitization. They end up with a sample of 696 matched pairs. It is worth noting that their research covers a longer period (1991–2007), more countries (140 countries) and various types of securitization (asset-backed securities (ABSs), mortgage-backed securities (MBSs), collateralized loan obligations (CLOs) and collateralized debt obligations (CDOs)), therefore they have more matched securitizing banks.

[13]We thank the referee for clarifying this point.

[14]Due to data limitation, we have little traceable information of SPVs in most securitization transactions. However, this argument is in line with anecdotal facts that SPVs do have an advantage as long as they are, indeed, truly bankruptcy remote and off balance sheet.

sources.

2.4. Estimation

To assess a bank's incentive in securitization, we examine the impact of tax rates and funding constraints on securitization, controlling for bank level variables, and country level macroeconomic and regulatory variables. Assuming each bank in our sample makes funding decisions individually based on the trade-off between costs and benefits of securitization, we observe zero securitization in the dependent variables when some banks find securitization unprofitable. In this sense, our sample is left-censored at zero. Therefore, we employ Tobit regressions as follows

$$\begin{aligned} SAR_{i,j,t} =& \alpha_1 CIT_{j,t} + \alpha_2 CIT_{j,t} \times Constrained_{i,j,(t-1)} + \alpha_3 Constrained_{i,j,(t-1)} \\ &+ \boldsymbol{\beta}'\mathbf{W}_{i,j,(t-1)} + \boldsymbol{\gamma}'\mathbf{Z}_{j,t} + \boldsymbol{\theta}'\mathbf{X}_{j,t} + \sum_t \delta_t T_t + \epsilon_{i,j,t} \end{aligned} \tag{2.6}$$

where i, j, t denotes the bank, the country and the year, respectively. The dependent variable, securitization asset ratio $SAR_{i,j,t}$, is defined as a ratio of the total amount of securitization to bank total assets for bank i in country j in year t ($SAR = \frac{ABS}{TA}$, where ABS stands for the total amount of ABS issuance and TA represents bank total assets). Specifically, the total amount of securitization is calculated by aggregating the amount of each ABS issuance for bank i in country j in year t. Moreover, a bank with its headquarter in jurisdiction j is subject to the corporate income tax rate $CIT_{j,t}$ in year t. In addition, $Constrained_{i,j,(t-1)}$ is a funding constraint dummy that takes the value one if bank i is classified as funding constrained in year $t-1$, and zero otherwise.

Our estimation rests on the definition of the funding constraint. In the previous model, a bank is classified as funding constrained if it has rich loans and poor deposits, and unconstrained otherwise. In practice, the loan to deposit ratio is frequently used to measure the relative abundance of investment opportunities to deposit capacities. Ideally, a bank having a high loan to deposit ratio is funding constrained and should look for extra liquidity. Hence, we define the funding constraint dummy based on the loan to deposit ratio in most specifications. In particular, the funding constraint dummy $D_{LoanToDeposit}$ takes the value one if a bank ranks in the upper quartile of the distribution of the loan to deposit ratios in each country, and zero otherwise.

To identify the tax effects on funding constrained and unconstrained banks, we interact the funding constraint dummy with tax rates, allowing tax incentives to vary depending on funding constraints. In particular, the sum of the coefficients α_1 and α_2 shows the tax effect on banks with substantial loan expansion opportunities but limited deposit resources, while α_2 by itself measures the sensitivity of funding unconstrained banks to corporate income taxes. If the sum of α_1 and α_2 is positive and significant, we could interpret it as evidence for the tax incentive at funding constrained banks to securitize. By contrast, funding unconstrained banks do not respond to tax rates when making securitization decisions according to the theoretical predictions. Hence, α_2 is expected to be insignificant.

As noted above, we have a vector of bank specific regressors, $\mathbf{W}_{i,j,(t-1)}$, including proxies of leverages, risks and performances[15]. First, *Equity/TA* represents a ratio of bank equity to total assets, measuring the leverage and capital adequacy of banks[16]. Calomiris and Mason (2004), Ambrose et al. (2005) and Pavel and Philis (1987) provide evidence that less capitalized banks try to reduce regulatory capital requirements through securitization. However, it is also likely that more solvent banks tend to securitize (Bannier and Hänsel 2008). Hence, the effect of bank capital on securitization is ambiguous. Next, we include *Z Score*, which is the sum of capital asset ratio and ROA divided by the standard deviation of ROA, to measure the credit risk of the bank. In particular, we use three-year rolling windows and take log transformation as in Laeven and Levine (2009). The sign of the relationship between credit risk and securitization is also far from

[15] We do not include the bank size into regressions since we have already considered the crucial effect of bank size on securitization and restricted our sample to large banks only.

[16] It is less likely that leverage leads to endogeneity bias in our analysis. First, in the model of Han et al. (2014) in the absence of securitization market, bank leverages are determined by loan and deposit market conditions as well as corporate tax rates. In the securitization decision, it is the trade-off of marginal costs of on and off-balance sheet financing, rather than bank leverage, that determines whether to securitize or not. Therefore, once we include tax rates, the funding constraint dummy, and the interaction of the two, it is unlikely our results are contaminated by omitted variable bias. We also control for other bank level variables, regulatory variables and macroeconomic variables to mitigate the concern of omitted variable bias. Second, securitization may affect bank leverage ex post as loans are removed from balance sheets and bank excess capital decreases. By contrast, in the model of Han et al. (2014) there is no channel through which leverages directly affect securitization. Therefore, we are less worried about reverse causality. In addition, we explicitly include bank leverages (*Equity/TA*) in our specifications to control for other possible channels through which leverages may directly or indirectly affect securitization, for instance regulatory capital arbitrage. Third, the average standard deviation of equity over total assets for each bank in our sample period is 1.09, indicating time-varying leverage. Therefore, the assumption of persistent leverage does not hold and hence endogeneity bias is less of concern. We are grateful to the referee for raising this point.

unanimous. Though Greenbaum and Thakor (1987) show that banks should securitize low risk assets, Panetta and Pozzolo (2010) find that risky banks transfer credit risk through securitization. Last, *ROA* is return on assets, which measures the operational performance of a bank. We expect efficient banks to be able to undertake securitization. All bank specific explanatory variables, including the funding constraint dummy, are lagged by one period to avoid a potential problem of endogeneity. To prevent extreme values from biasing our empirical results, we winsorize the bank specific variables at the 1% and 99% levels.

We also include a set of macroeconomic control variables, $\mathbf{Z}_{j,t}$. We consider *GDP per capita 2005*, *GDP per capita Growth* and *Inflation* to capture the level of economic development, income growth and inflation, respectively. In particular, high growth rates of GDP per capita are expected to boost credit expansions, which further fuel securitization. Next, we include *Traded Stock/GDP*, which measures the volume of stock traded as a percentage of GDP, indicating the level of financial development. We expect banks in highly developed financial systems to securitize more assets. Moreover, we control for the competition in the banking sector, *Bank Concentration*. As securitization transactions are mostly dominated by large banks, we expect that large banks in highly concentrated markets tend to securitize more assets.

As our sample includes banks operating in heterogeneous banking systems, we need to control for regulatory and supervisory differences, $\mathbf{X}_{j,t}$. In particular, we do not use country fixed effects which eliminate the bulk of variations in corporate income tax rates across countries. Instead, we use explicit indicators of bank regulation and supervision. First, we include a dummy indicating risk related capital requirements. *Risk Related Capital Ratio* takes the value one if the country adopts the minimum capital ratio that varies as a function of an individual bank's credit risk, and zero otherwise. Second, we include a variable of official supervisory actions, *Multiple Supervisory Bodies*, indicating single or multiple supervisory authorities for banks. Next, we include an indicator of private monitoring. *Disclosure Risk Management* implies whether it is compulsory for banks to disclose risk management procedure to the public. Depositors could monitor banks better if risk management procedures are publicly known and accessible. Similarly, deposit insurance may affect banks' risk taking and securitization, hence we include a dummy *Explicit Deposit Insurance* that distinguishes between explicit and implicit deposit insurance systems. Last, we include *Restrictions on Real Estate* that depict the degree of regulatory restrictiveness for banks engaging in real estate investment, development and management. Such restrictions may directly affect banks' involvement in mortgage and off-balance sheet activities.

Our regressions include year dummies T_ts that capture common macroeconomic shocks to all banks within the same year, for instance business cycles. ε_{ijt} is an error term. Finally, in all specifications, we cluster heteroscedasticity robust standard errors at the bank level, and our results continue to hold when clustering standard errors at the country level.

Table 2.1 tabulates the distributions of banks, securitizing banks and ABS issuance across countries[17]. It is worth noting that U.S. banks account for two thirds of our bank sample. Additionally, the ABS market in U.S. has been the largest in the world. Moreover, Table 2.1 displays geographic variations in SARs and effective tax rates as well. In particular, Australian, Dutch and Spanish banks present pretty high SARs. Presenting the time distribution of banks, securitizing banks and ABS issuance, Table 2.2 suggests that securitization markets have been growing and more banks have been involving in asset securitization over time. In addition, Table 2.2 plots the evolution of SARs and tax rates. Finally, Table 2.3 displays summary statistics of all variables. Notably, the securitization asset ratio has a mean of 0.26% in our sample[18]. In addition, effective marginal tax rates are generally smaller than statutory tax rates.

2.5. Empirical Results

In this section, we present the results of regressions. First, we look at the tax effects on funding constrained and unconstrained banks in the benchmark regressions, controlling for bank specific variables, macroeconomic and regulatory variables. Next, we conduct a number of robustness checks by splitting our sample into funding constrained and unconstrained banks, adopting alternative dependent variables adjusted for off-balance sheet items, using a restricted sample of non-U.S. banks, using alternative measures

[17]Securitizing banks are defined as banks that issues asset-backed securities.

[18]The small sample means of SAR and SAR_{adj} are primarily driven by the large group of nonsecuritizing banks (4158 banks or 94% of our sample). The means of SAR and SAR_{adj} are 7.7% and 5.9% for the group of securitizing banks, which are reasonable.

of funding constraints, using statutory tax rates, and adopting weighted tax rates for multinational banks.

2.5.1. Baseline Results

Table 2.4 presents the main results of this study. We report the estimated marginal effects at variable means rather than regression coefficients which are not straightforward to interpret. The first column presents the results for the benchmark regression. In accordance with Hypothesis 2, we have an insignificant coefficient α_1 for the variable of tax rates, indicating no tax effect at funding unconstrained banks. By contrast, the estimated coefficient α_2 for the interaction between corporate income tax rates and the funding constraint dummy is positive and statistically significant. Furthermore, the sum of α_1 and α_2 is positive and highly significant, consistent with the prediction in Hypothesis 1 that higher corporate income taxes create an incentive for funding constrained banks to securitize assets. Specifically, the sum of the marginal effects of α_1 and α_2 is 0.09, indicating that a one percentage point rise in corporate income tax rates raises the securitization asset ratio by 0.09%. Put differently, relative to the average securitization asset ratio of 0.26% in our sample, a one standard deviation rise of tax rates (4.02 percentage points) increases the securitization intensity by 1.4% $(= 4.02 \times 0.09 \div 0.26)$, which is economically significant.

Among bank specific variables, we find that the estimated marginal effect for the bank leverage is negative and significant. This finding supports the regulatory capital arbitrage story that less capitalized banks tend to securitize more assets to set free capital. Moreover, we find that risky banks of a low *Z score* securitize more assets, possibly for the sake of transferring credit risk. Finally, we find that banks with a higher *ROA* securitize more assets, reflecting that efficient banks are capable of securitizing assets. As for macroeconomic control variables, the regression output indicates that banks headquartered in countries of a lower level of economic development but higher economic growth and more advanced financial markets, tend to securitize more assets. With regard to regulatory and supervisory institutions, we find that risk related capital requirements promote securitization, whereas multiple supervision bodies and explicit deposit insurance systems have negative impacts on securitization.

2.5.2. Robustness checks

To relax the restrictions of identical coefficients of bank specific variables, macroeconomic variables and regulatory variables for funding constrained and unconstrained banks in the benchmark regression, we divide our sample into two corresponding subsamples. We present the output of the separate Tobit regressions in columns 2 and 3. In line with our predictions, we identify tax effects for the funding constrained banks only. In addition, reported in the last row, our results reject the null hypothesis that tax effect is no greater in the constrained subsample than that in the unconstrained subsample. We conclude that corporate income taxes have greater impacts on the "loan-rich, deposit-poor" banks than on the "loan-poor, deposit-rich" banks. For brevity, we report variables of interest only and do not report the marginal effects on bank level, macroeconomic level and regulatory variables for subsequent tables.

One possible caveat to our previous specifications is that the denominator of the dependent variable, bank total assets, does not include off-balance sheet items. To show our analysis are not biased by the construction of the dependent variable, we define an adjusted securitization asset ratio $SAR_{adj} = \frac{ABS}{TA+ABS}$, assuming that the ABS outstanding issuance largely captures the scale of off-balance sheet items[19]. Therefore, the adjusted securitization asset ratio can control for both on-and off-balance sheet items. As reported the results in column 4 of Table 2.4, the results continue to support our predictions.

A concern with our sample is that U.S. banks account for more than two thirds, although our sample contains banks with headquarters in 19 OECD countries. Additionally, U.S. has the largest ABS market, accounting for roughly 70% of global issuance. To rule out the scenario that our results are driven by a single country, we exclude U.S. banks for fear of its over-representation. Consequently, our results continue to hold in the non-U.S. sample as in column 1 in Table 2.5 we document a significant tax distorting effect at the funding constrained banks and nil tax effect at the unconstrained banks.

In the previous specifications, we define the funding constraint dummy relying on the loan to deposit ratios. Alternatively, we construct a new measure of funding constraint dummy based on growth rates of loans and market shares of deposits. In particular, we generate a dummy $D_{LoanGrowth}$ that indicates whether a bank ranks in the upper

[19]We thank the referee for suggesting this alternative dependent variable.

quartile in the distribution of loan growth rates in a given country. Similarly, we generate a dummy $D_{DepositShare}$ that indicates whether a bank ranks in the lower quartile in the distribution of deposit market shares in a given country. Next, the alternative funding constraint dummy $D_{LoanGrowth} \times D_{DepositShare}$ is a product of these two dummies and takes the value one if a bank has a relatively high growth rate of loans and a relatively small market share of customer deposits. In column 2 we present the regression output, adopting $D_{LoanGrowth} \times D_{DepositShare}$ as the funding constraint dummy. Again, the marginal effect of tax rates is insignificant whereas the sum of the marginal effects of the tax rates and the interaction term remains positive and highly significant, consistent with our hypotheses.

Instead of using deposit market shares, we again rely on deposit interest rates and loan growth rates to define funding constraints in column 3. Though absolute prices are not good proxies for competition, deposit interest rates directly measure the cost of deposit financing. We expect banks paying higher deposit rates to have stronger incentives to securitize. We calculate the deposit interest rates by dividing deposit interest expenses over total deposits and generate a dummy $D_{DepositInterest}$ that indicates whether a bank ranks in the upper quartile in the distribution of deposit rates in a given country. Likewise, the alternative funding constraint dummy $D_{LoanGrowth} \times D_{DepositInterest}$ is a product of $D_{LoanGrowth}$ and $D_{DepositInterest}$ and takes the value one if a bank has a relatively high growth rate of loans and pays relatively high deposit interest rates. We find qualitative similar results that support our predictions.

All the results presented so far are based on effective marginal tax rates of corporate income taxes. In column 1 of Table 2.6, we use statutory tax rates instead. Consequently, we have largely unchanged results. In particular, the marginal effect of tax rates is insignificant while the marginal effect of the interaction term is positive and significant. Overall, the sum of the two marginal effects is positive and significant, indicating funding constrained banks securitize more assets when faced with higher corporate income tax rates.

As our sample includes a number of large, multinational banks whose revenues from different foreign subsidiaries are likely to be subject to different corporate income tax schemes, we address this issue by constructing income-weighted tax rates for multinational banks. The idea is to use the share of the operating income from each foreign subsidiary as weights to calculate a weighted tax rate that applies to the parent company. As a result, the weighted tax rate is bank-specific, depending on both the geographic and income distribution of foreign subsidiaries. For simplicity, we ignore practical issues such as tax credit and tax treaties between home and host countries. The formula for calculating the income-weighted tax rates is as follow:

$$\begin{aligned} WCIT_{OperatingIncome_{p,t}} = & \sum_f \frac{OperatingIncome_{f,t}}{OperatingIncome_{p,t}} \times CIT_{f,t} \\ & + (1 - \sum_f \frac{OperatingIncome_{f,t}}{OperatingIncome_{p,t}}) \times CIT_{h,t} \end{aligned} \tag{2.7}$$

where $WCIT_{OperatingIncome_{p,t}}$ is an income-weighted tax rate for parent company p in year t. The weight is determined by the income share of foreign subsidiaries f as well as home subsidiaries h. We define *OperatingIncome* as a sum of net interest revenues and other operating income. Additionally, $CIT_{f,t}$ and $CIT_{h,t}$ denote corporate income tax rates in foreign countries and home country, respectively. In the end, we adopt the income-weighted tax rates for multinational banks and retain the original tax rates for banks operating within a single country. Due to the problem of missing values of operating income, we have the operating income-weighted tax rates for 60 multinational banks only. The weighted tax rates are largely close to the original tax rates. We present the output of the regression using operating income-weighted tax rates in column 2. The results continue to support our hypotheses. As a robustness check, we also calculate operating profit-weighted tax rates, $WCIT_{OperatingProfit}$, using the same approach. The distorting effects of corporate income taxes documented in the last column are significant and comparable to that using operating income-weighted tax rates.

2.6. Concluding Remarks

"The evidence strongly suggests that without the excess demand from securitizers, subprime mortgage origination (undeniably the original source of crisis) would have been far smaller and defaults accordingly far fewer" (Alan Greenspan's testimony to the House Committee on Oversight and Government Reform 2008). Therefore, a clear understanding of the motives behind banks' surging supply of asset securitization is crucial. The current debate on securitization has resulted in fruitful discussions about how to improve bank regulation. For instance, BIS (2011) proposed new measures, such as revised capital requirements and liquidity coverage ratios, to improve bank supervision. However, insufficient attention has been paid to tax systems. Besides, the debate on the role of taxation in the crisis has been restricted to excess leverages and distorted investments towards home ownership by certain income tax rules that fueled the housing bubbles (Keen 2011; Shaviro 2011).

Along with Han et al. (2014), we document the tax distorting effects on securitization in a sample of OECD banks over the period from 1999 to 2006. Consistent with the theoretical predictions, we find that banks with substantial loan origination capacities but little deposit market power are more likely to securitize and securitize more assets in a higher tax regime. This tax distorting effect is economically and statistically significant in all specifications. By contrast, corporate income taxation does not affect securitization at funding unconstrained banks. Our results are robust to various sensitivity tests.

Our analysis have direct policy implications. Given the tax arbitrage has already contributed to excessive growth of securitization, we may need to address the tax distortions in current corporate income tax systems. One possible solution would be to introduce an Allowance for Corporate Equity (ACE) system that allows a deduction for returns on equity as well (Keen 2011). The ACE systems have been applied in Belgium and are expected to get rid of tax penalty on capital reserves as well as asymmetric tax treatment between on-and off-balance sheet financing. This neutralized tax treatment might not only contain excess leverage, but also alleviate the tax disadvantage of on-balance sheet financing for funding constrained banks and therefore prevent their excessive securitization and risk taking. In addition, the proposal of levying new taxes on banks may intensify distortions and therefore seems inappropriate. In 2009, Liberal Democrats proposed an extra tax of 10 percent on bank profits, in order to pay off UK's public deficit. Moreover, the Financial Activities Tax (FAT) levied on the sum of bank profits were laid out in the International Monetary Fund interim report in 2010 in response to the subprime financial crisis. Although FAT was expected to discourage undesirable risk taking and to raise additional revenues to pay for bailouts (IMF 2010), in our point of view the new taxes on banks could further distort banks' incentive to engage in securitization and generate adverse effects on banks and securitization markets.

In particular, in order to lower financing cost and to satisfy funding demand, banks are inclined to securitize more assets than the optimal amount, contributing to excessive securitization that threatens the safety and soundness of banking.

Table 2.1: Country distributions

Country	No. of banks	No. of securitizing banks	ABS (bn USD)	SAR	ECIT
Australia	6	6	37.712	1.838	27.061
Austria	64	1	0.650	0.001	26.881
Belgium	18	4	15.869	0.380	26.627
Canada	21	7	16.578	0.137	29.751
France	83	11	97.430	0.071	26.617
Germany	543	10	158.359	0.010	33.817
Ireland	6	4	12.594	0.415	9.362
Italy	187	42	80.715	0.429	31.359
Japan	196	15	26.340	0.022	37.094
Mexico	13	2	1.350	0.050	20.575
Netherlands	14	8	128.914	1.439	27.897
Portugal	11	5	19.072	0.649	23.669
South Korea	4	2	1.497	0.066	18.873
Spain	54	32	195.696	1.353	30.663
Sweden	26	1	0.179	0.002	20.298
Switzerland	107	2	326.589	0.056	16.857
Turkey	12	6	8.646	0.430	11.021
UK	44	15	538.166	0.341	24.641
US	3014	92	2679.768	0.311	32.989
Sum	4423	265	4346.122	0.264	25.044

Table 2.2: Time distributions

Year	No. of banks	No. of securitizing banks	ABS (bn USD)	SAR	ECIT
1999	1608	75	127.126	0.511	26.742
2000	2119	97	190.564	0.305	26.225
2001	3569	117	291.033	0.210	25.636
2002	3700	113	376.681	0.184	25.635
2003	3692	116	554.439	0.263	24.880
2004	3692	107	634.964	0.207	24.570
2005	3631	121	939.178	0.272	23.827
2006	3230	128	1232.138	0.323	22.753

Table 2.3: Descriptive Statistics

Variables	N	Mean	Std. Dev.	1%	Median	99%
SAR	25232	0.26	3.24	0.00	0.00	5.78
SAR_{adj}	25232	0.20	1.98	0.00	0.00	5.47
$ECIT$	25232	32.02	4.02	15.39	32.99	40.89
$SCIT$	25228	38.67	4.18	24.10	39.30	52.03
$WCIT_{OperatingIncome}$	25232	32.20	4.02	15.39	32.99	40.89
$WCIT_{OperatingProfit}$	25232	32.20	4.03	15.39	32.99	40.89
Loan to Deposit Ratio	25232	97.98	61.18	16.70	89.10	353.36
Deposit Interest Rate	24722	3.01	6.10	0.13	2.80	7.11
Loan Growth	24517	13.58	35.55	-28.77	8.31	128.60
Deposit Market Share	25232	0.45	2.30	0.00	0.01	12.18
Bank Size	25232	18.17	90.27	0.26	1.23	437.51
Z Score	25232	4.36	1.17	1.29	4.37	7.09
Equity/TA	25232	8.52	5.06	2.57	8.05	24.12
ROA	25232	0.94	1.10	-0.95	0.91	3.88
GDP per capita 2005	25232	10.57	0.19	10.04	10.63	10.83
GDP per capita Growth	25232	1.68	1.18	-0.49	1.81	3.99
Inflation	25232	2.31	1.74	-0.80	2.27	3.52
Traded Stock/GDP	25232	159.55	82.15	5.50	157.65	309.65
Bank concentration	25232	39.92	21.40	21.40	29.82	91.91
Risk Related Capital Ratio	25232	0.35	0.48	0	0	1
Multiple Supervisory Bodies	25232	0.74	0.44	0	1	1
Disclosure Risk Management	25232	0.31	0.46	0	0	1
Explicit Deposit Insurance	25232	1.00	0.04	1	1	1
Restrictions on Real Estate	25232	3.28	1.27	1	4	4

Notes: *Bank Size* is expressed in billion USD. *GDP per capita 2005* is the log of GDP per capita in 2005 USD. *Risk Related Capital Ratio*, *Disclosure Risk Management*, *Disclosure Risk Management*, and *Explicit Deposit Insurance* are dummy variables. *Restrictions on Real Estate* is a scale variable from 1 to 4, with larger numbers indicating greater restrictiveness. The rest variables are expressed as a percentage.

Table 2.4: Baseline Regressions

The dependent variables are securitization asset ratios (SAR) in columns 1 to 3, and adjusted securitization asset ratio (SAR_adj) in column 4. Columns 1 and 4 show the results for our full sample. Columns 2 and 3 show the results for the subsample of funding constrained banks only and funding unconstrained banks only, respectively. In addition, we report the test results of whether the sum of α_1 and α_2 is positive and significant for the full sample. In the end, we report the test results of whether α_1 of the constrained subsample is greater than α_1 of the unconstrained subsample. Overall, we report the estimated marginal effects at variable means. Standard errors are adjusted for clustering at the bank level and reported in parentheses below the marginal effects. Marginal effects of year dummies are not reported.

	(1) SAR	(2) SAR	(3) SAR	(4) SAR_adj
ECIT	0.021	0.138***	0.013	0.015
	(0.026)	(0.049)	(0.021)	(0.017)
$ECIT \times D_{LoanToDeposit}$	0.068***			0.044***
	(0.025)			(0.016)
$D_{LoanToDeposit}$	-0.800			-0.497
	(0.667)			(0.443)
Equity/TA	-0.134***	-0.253***	-0.062**	-0.089***
	(0.035)	(0.080)	(0.026)	(0.021)
Z Score	-0.383***	-0.557***	-0.283***	-0.250***
	(0.087)	(0.169)	(0.092)	(0.051)
ROA	0.849***	1.610***	0.412**	0.566***
	(0.190)	(0.375)	(0.207)	(0.114)
GDP per capita 2005	-0.988***	-2.950***	-0.446	-0.684***
	(0.353)	(0.843)	(0.294)	(0.229)
GDP per capita Growth	0.190***	0.341***	0.114**	0.125***
	(0.059)	(0.131)	(0.053)	(0.037)
Inflation	0.012	-0.001	0.008	0.008
	(0.024)	(0.058)	(0.021)	(0.016)
Traded Stock/GDP	0.008***	0.015***	0.005***	0.006***
	(0.002)	(0.004)	(0.001)	(0.001)
Bank concentration	0.005	0.007	0.002	0.003
	(0.006)	(0.013)	(0.005)	(0.004)
Risk Related Capital Ratio	0.493***	0.416	0.408**	0.325***
	(0.185)	(0.383)	(0.176)	(0.116)
Multiple Supervisory Bodies	-3.076***	-3.902***	-2.445***	-2.067***
	(0.582)	(0.966)	(0.688)	(0.333)
Disclosure Risk Management	-0.357	-0.438	-0.307	-0.238
	(0.262)	(0.597)	(0.225)	(0.172)
Explicit Deposit Insurance	-3.339***	-3.769*	-2.844**	-2.278***
	(1.174)	(1.972)	(1.223)	(0.801)
Restrictions on Real Estate	0.015	-0.006	0.010	0.011
	(0.091)	(0.176)	(0.082)	(0.060)
P-value of H_1: $\alpha_1 + \alpha_2 > 0$	0.000			0.000
P-value of H_1: α_1 in the constrained subsample > α_1 in the unconstrained subsample		0.000		
Year Dummies	Yes	Yes	Yes	Yes
Std. Err. clustered at Banks	Yes	Yes	Yes	Yes
Pseudo R^2	0.09	0.06	0.08	0.09
Observations	25,232	6,329	18,903	25,232

Table 2.5: Robustness Checks

The dependent variables are securitization asset ratios (SAR). Column 1 shows results for the regression of the non-U.S. sample. Column 2 shows results for the regression using the funding constraint dummy based on deposit shares and loan growth. Column 3 shows results for regression using the funding constraint dummy based on deposit interest rates and loan growth. In the end, we report the test results of whether the sum of α_1 and α_2 is positive and significant for the full sample. Overall, we report the estimated marginal effects at variable means. Standard errors are adjusted for clustering at the bank level and reported in parentheses below the marginal effects. Marginal effects of bank level, macroeconomic and regulatory variables, and year dummies are not reported.

	(1) SAR	(2) SAR	(3) SAR
$ECIT$	0.009	0.033	0.046
	(0.009)	(0.026)	(0.028)
$ECIT \times D_{LoanToDeposit}$	0.013*		
	(0.008)		
$D_{LoanToDeposit}$	-0.052		
	(0.230)		
$ECIT \times D_{LoanGrowth} \times D_{DepositShare}$		0.057**	
		(0.027)	
$D_{LoanGrowth} \times D_{DepositShare}$		0.063	
		(0.793)	
$ECIT \times D_{LoanGrwoth} \times D_{DepositInterest}$			0.113***
			(0.030)
$D_{LoanGrowth} \times D_{DepositInterest}$			-2.190***
			(0.620)
P-value of H_1: $\alpha_1 + \alpha_2 > 0$	0.009	0.004	0.000
Bank controls	Yes	Yes	Yes
Macroeconomic and Regulatory controls	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Std. Err. clustered at Banks	Yes	Yes	Yes
Pseudo R^2	0.11	0.09	0.07
Observations	8,836	24,227	24,451

***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2.6: Alternate tax rates

The dependent variables are securitization asset ratios (SAR). Column 1 shows results for the regression using statutory tax rates. Column 2 and 3 show results of the regression using operating income-weighted tax rates and operating profit-weighted tax rates, respectively. In the end, we test of whether the sum of α_1 and α_2 is positive and significant for the full sample. Overall, we report the estimated marginal effects at variable means. Standard errors are adjusted for clustering at the bank level and reported in parentheses below the marginal effects. Marginal effects of bank level, macroeconomic and regulatory variables, and year dummies are not reported.

	(1) SAR	(2) SAR	(3) SAR
$SCIT$	-0.016		
	(0.028)		
$SCIT \times D_{LoanToDeposit}$	0.069**		
	(0.027)		
$WCIT_{OperatingIncome}$		0.021	
		(0.026)	
$WCIT_{OperatingIncome} \times D_{LoanToDeposit}$		0.065***	
		(0.025)	
$WCIT_{OperatingProfit}$			0.018
			(0.026)
$WCIT_{OperatingProfit} \times D_{LoanToDeposit}$			0.058**
			(0.025)
$D_{LoanToDeposit}$	-1.197	-0.712	-0.502
	(0.839)	(0.667)	(0.684)
P-value of H_1: $\alpha_1 + \alpha_2 > 0$	0.025	0.001	0.003
Bank controls	Yes	Yes	Yes
Macroeconomic and Regulatory controls	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Std. Err. clustered at Banks	Yes	Yes	Yes
Pseudo R^2	0.08	0.09	0.09
Observations	25,228	25,232	25,232

***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

APPENDIX

Table A.1: Data Descriptions and Sources

Variables	Descriptions	Sources
SAR	Securitization asset ratio, defined as a ratio of the total amount of ABS issuance to bank total assets, is the dependent variable in Tobit regressions.	ABS Alert and Bankscope
SAR_{adj}	Adjusted securitization asset ratio, defined as $\frac{ABS}{TA+ABS}$, where ABS stands for the total amount of ABS issuance and TA represents bank total assets.	ABS Alert and Bankscope
ECIT	Effective marginal tax rates of corporate income taxes which measure the percentage of changes in a bank's tax obligation as income rises.	Based on the OECD tax database
SCIT	Statutory tax rates of corporate income taxes.	The OECD tax database
$WCIT_{OperatingIncome}$	Corporate income taxes weighted by operating income. The weight is determined by the share of operating income from foreign subsidiaries.	The OECD tax database, Bankscope
$WCIT_{OperatingProfit}$	Corporate income taxes weighted by operating profits. The weight is determined by the share of operating profits from foreign subsidiaries.	The OECD tax database, Bankscope
$D_{LoanToDeposit}$	The funding constraint dummy that takes the value one if a bank is in the upper quartile of the distribution of the loan to deposit ratios in each country, and zero otherwise. Lagged by one period.	Bankscope
$D_{LoanGrowth} \times D_{DepositShare}$	The funding constraint dummy that takes the value one if a bank is in the upper quartile of the distribution of the loan growth rates and in the lower quartile of the distribution of the deposit market shares in each country, and zero otherwise. Lagged by one period.	Bankscope
$D_{LoanGrowth} \times D_{DepositInterest}$	The funding constraint dummy that takes the value one if a bank is in the upper quartile of the distribution of the loan growth rates and deposit interest rates in each country, and zero otherwise. Lagged by one period.	Bankscope
Equity/TA	Ratio of bank equity to total assets. Lagged by one period.	Bankscope
Z Score	Index of bank solvency risk which is constructed as $\frac{ROA+CAR}{SD(ROA)}$ and calculated using three-year rolling windows, where ROA stands for return on assets, CAR represents capital asset ratio and $SD(ROA)$ refers to the standard deviation of ROA.	Bankscope
ROA	Return on assets. Lagged by one period.	Bankscope
GDP per capita 2005	GDP per capita (constant 2005 USD).	WDI
GDP per capita Growth	Annual growth rates of real GDP per capita.	WDI
Inflation	Annual growth rates of the GDP implicit deflator.	WDI
Traded Stock/GDP	The volume of stock traded as a percentage of GDP.	WDI

Bank Concentration	Market concentration in the banking sector in a given country.	GFDD
Risk Related Capital Ratio	Dummy variable indicating that minimum capita ratio varies as a function of an individual bank's credit risk.	Bank Regulation and Supervision Surveys and Databases
Multiple Supervisory Bodies	Dummy variable indicating multiple supervisory bodies for banks.	Bank Regulation and Supervision Surveys and Databases
Disclosure Risk Management	Dummy variable indicating that it is compulsory for banks to disclose risk management procedures to the public.	Bank Regulation and Supervision Surveys and Databases
Explicit Deposit Insurance	Dummy variable indicating an explicit deposit insurance system.	Bank Regulation and Supervision Surveys and Databases
Restrictions on Real Estate	Degree of regulatory restrictiveness for banks engaging in real estate investment, development and management on a scale from 1 to 4, with larger numbers indicating greater restrictiveness.	Bank Regulation and Supervision Surveys and Databases

Chapter 3

Securitization and Economic Activity: The Credit Composition Channel

3.1. Introduction

Securitization is an important feature of modern financial systems. Starting in the early 60s, securitization of mortgage loans became first common in the U.S. Securitization steadily became more widespread until the 2000s, when it reached around 50% of outstanding mortgage and consumer loans in the U.S. The years prior to the crisis of 2007-2009 were then characterized by a boom in worldwide securitization markets. Between 2000 and 2006, issuance of securitization products more than tripled, from less than $700 billion to about $2.800 billion[20]. The crisis then caused an effective breakdown of securitization markets. Securitization activities retreated to levels only seen before the 2000s and have stabilized at a low level since then.

Amid the carnage, a discussion has emerged about the future of securitization. Several policy-makers have spoken out against, but also in favor of securitization markets. Recently, the European Central Bank and the Bank of England (2013) have issued a paper stating their intention to revive securitization markets, focusing on the high quality segment of the ABS market.

Clearly, there are economic benefits and costs to securitization. First and foremost, securitization allows banks to shift risk off their balance sheet and frees up capital for new lending. Securitization is also an important risk management tool, allowing banks to achieve a more diversified pool of exposures. This should lower their cost of taking on risks, the benefit of which should, at least partially, be passed on to borrowers in the form

[20]Sources: the Flow of Funds database and the AB Alert and CM Alert databases.

of more favorable lending conditions and higher credit availability. Securitization also allows banks to better insulate themselves from funding shocks, potentially stabilizing credit extension.

On the downside, securitization has demonstrated the potential to worsen the efficiency of financial intermediation. The main reason is the presence of informational problems. In particular, banks, which tend to securitize, become less exposed to borrower risk, which undermines their incentives to screen and monitor. This may result in lower quality lending, and erodes the benefits of intermediation – relative to market-financing. High complexity has also been identified as a potential cost to securitization, as it reduces the ease with which outsiders can evaluate securitization products, potentially resulting in inefficient investment decisions.

There is significant body of evidence supporting the idea that securitization affects intermediation. The literature has typically focused on the impact of securitization on banks themselves (such as their lending behavior or their risk-taking), the impact on loan conditions (e.g., the pricing of loans) and the impact on borrowers (such as their likelihood of default). This focus on the micro-level has clear advantages in providing good settings for identification.

In this paper we consider the relationship between securitization and *aggregate* outcomes, in particular economic activity. While identification is more challenging at the aggregate level, this focus offers distinct advantages. Securitization is likely to be associated with important externalities that cannot be captured by micro-studies. For example, while securitization may very well increase profits and lower risk for the bank that is shedding the risk, it may be detrimental to the buyers of securitization products. In addition, securitization may also affect the efficiency of capital allocation in the economy (it can either increase or decrease it), which has implications that will not be visible at the immediate bank-firm nexus.

Specifically, in this paper we exploit country-level variations in securitization activities to analyze the relationship between securitization and economic aggregates. Based on a large international sample of securitization issuances from 1995 to 2012, we find securitization activities to be negatively correlated with proxies for economic activity, such as GDP per capita growth, capital formation and changes in new firm establishments. The effect is economically significant and is not driven by the period of the Global Financial Crisis, suggesting that it is a structural property of securitization.

What can explain this finding? Our results indicate that the effect is neither driven by the amount nor the quality of credit in the economy, which rules out most of the common channels for why securitization affects macroeconomic outcomes. We put forward a new channel, based on the idea that securitization affects the aggregate *composition* of credit in the economy. Securitization of residential mortgage and consumer loans (which are more homogenous and less information sensitive) is easier than for business loans. The development of securitization is thus expected to broadly favor loans to households, as opposed to loans to business. As both types of borrowers are competing for an economy's scarce resources, this may result in an aggregate reduction in investment and lower economic activity[21].

The data is broadly consistent with the *credit composition channel.* We show that only securitization of loans to households is negatively related to economic activity. Securitization of business loans instead displays as a positive association with economic activity, albeit a weak one. In addition, we find that securitization increases an economy's consumption-investment ratio. Furthermore, securitization has a more pronounced (negative) impact on proxies of the supply side of the economy than on economic growth. This is consistent with a shift from investment to consumption constraining the supply side of the economy, while potentially boosting demand (and hence leading to a more muted impact on GDP).

The remainder of this paper is organized as follows. The following section discusses various channels that have been emphasized in the literature and through which securitization may affect economic activity. We relate them to the *credit composition channel* and form hypotheses. Section 3.3 describes the data and the empirical methodology. Section 3.4 contains the empirical results. The final section concludes and discusses implications for policy.

[21] Consistent with the different implication for economic activity, Beck et al. (2012) show that, for a sample of developed and developing economies, enterprise credit facilitates economic growth whereas household credit has no impact on growth. Sassi and Gasmi (2014) , studying 27 European countries, find that enterprise credit is positively related to economic growth whereas household credit has a negative effect.

3.2. Securitization and Economic Activity: Channels and Hypotheses

To evaluate the relationship between securitization and economic activity on macro level, one should first understand the dynamics of securitization at micro level: Why are banks and other financial institutions (and also some non-financial institutions) securitizing? In an early contribution, Greenbaum and Thakor (1987) theoretically show that in a frictionless environment (with full information and no regulation) securitization funding and deposit funding are identical, but they also show how public policy, regulation and information asymmetry change this. The literature proposes regulatory capital arbitrage, gaining extra liquidity, better bank performance and more efficient risk sharing (risk transfer) as driving factors behind securitization (see Cardone-Riportella et al. (2010) for a summary of the empirical literature). The empirical findings, however, are rather mixed. On one hand, Panetta and Pozzolo (2010), for instance, find that the results of securitization are ex-post in line with the expectations (securitizing banks increased their capital ratios and reduced their riskiness) in a cross-country bank level analysis. Again, using individual bank data Affinito and Tagliaferri (2010) find that banks once they securitize have higher profits and lower bad loans. On the other hand, in their study with U.S. bank data and propensity score matching technique, Casu et al. (2013) conclude that first-time securitizing banks would have comparable costs of funding, credit risk and profitability if they would not securitize. A crucial point is the complexity of these financial instruments. Creating a high fixed cost to originate securities, this complexity is a barrier to enter the securitization market (Panetta and Pozzolo, 2010), but there are no effective barriers to buy these highly sophisticated securities and participate the market as a buyer rather than originator.

The literature on dynamics of securitization almost exclusively focuses on bank level securitization[22]. Many papers touch upon the factors explaining country level securitization. The importance of legal framework regarding securitization is raised both in Maddaloni and Peydro (2011) and Altunbas et al. (2009). Altunbas et al. (2009) emphasize the importance of legal origin (common vs. civil law with the common law no requiring any legal background for securitization). Maddaloni and Peydro (2011)

[22] An exception is Peersman and Wagner (2015). Using structural identification of different types of financial shocks based on sign restrictions, they find that innovations in securitization markets have important effects for U.S. business cycles.

use legal obstacles to securitization in European countries as time invariant instruments (similar to legal origin). Other main factors mentioned in the literature are demand from investors (including foreign investors), banks' transition to market-based funding from deposit funding, financial innovation and the role of government in some specific cases like the US (Panetta and Pozzolo, 2010, Altunbas et al. 2009; ECB, 2011).

The decision to securitize at the bank (or firm) level may affect the real economy beyond the securitizing institution through different channels. The channels emphasized by previous literature can be broadly categorized into two groups, depending on how they may potentially affect economic output.

First, there are channels suggesting that securitization changes *credit volume* in the economy. This may, in turn, lead to more economic activity if it alleviates financing constraints of firms. To the contrary, it may also reduce economic activity if it causes excessive debt burdens and defaults. There are various reasons for why securitization activities are expected to affect the amount of credit in the economy, or more broadly, lending conditions. Securitization lowers the risks on banks' balance sheets and allows to free economic and/or regulatory capital[23]. This should encourage banks to increase their lending activities and charge lower rates to borrowers. Nadauld and Weisbach (2012) provide micro-evidence for this, showing that securitization in the form of CLOs lowers the price of corporate debt. Moreover, securitization techniques allow banks to improve their risk management, which should reduce the cost of taking on risk. Loutskina and Strahan (2009) find that in the U.S. securitization lowers the impact of funding shocks to loan supply and Carbo-Valverde et al. (2015) show reduced credit constraints for Spanish firms working with banks involved in ABS securitization before the recent financial crisis. More broadly, there is evidence that banks pass on risk management benefits from credit risk transfer techniques to borrowers (Cebenoyan and Strahan (2004), Franke and Krahnen (2005), Hirtle (2009) and Norden, Buston and Wagner (2014)).

Second, there are channels suggesting that securitization has a macroeconomic impact by affecting *credit quality*. By reducing constraints at the side of banks, securitization should lead to a more efficient allocation of capital in the economy (that is, capital flows to the most productive firms and risk is efficiently spread among a diverse group of

[23]Securitization may also be driven by regulatory capital arbitrage in case there remains implicit recourse on securitizers (Acharya et al. 2013), or when it leads to asset substitution (Jones (2000) and Agostino and Mazzuca (2011)).

investors). Stein (2010), in particular, argues that securitization enhances the allocation of risks by transferring them from banks to outside investors. On the downside, there is evidence that securitization reduces credit quality by undermining monitoring and screening incentives of banks[24]. Marsh (2006) finds that the announcement effect of a new bank loan is weakened when a bank actively uses securitization techniques, consistent with informational problems. Keys et al. (2010) show that securitization has negative effects on the screening incentives of lenders. However, Agarwal et al. (2012) find no evidence of adverse selection in default risk in mortgage securitizations, whereas Benmelech et al. (2012) find that adverse selection problems in corporate loan securitizations are less severe than commonly believed.

The *credit volume* and *credit quality channel* of securitization are also echoed in the literature on financial development (starting from King and Levine (1993) and surveyed in Levine (2005)). While we focus here on a specific type of financial innovation, this literature studies financial development more broadly. It emphasizes that financial development can have a positive impact on economic growth by reducing financing constraints (akin to the *credit volume channel*) and by affecting the efficiency of intermediation and the allocation of capital in the economy (the *credit quality channel*).

In this paper we emphasize a new channel, which we term the *credit composition channel* of securitization. Household loans, especially mortgages, are more homogenous and can hence more readily be used as collateral in securitization pools (Loutskina, 2011). This is in contrast to business loans, which typically are also more relationship-based. Business loans require more monitoring and screening and are less easily securitized without causing efficiency losses. We would thus expect that general developments in securitization techniques have a bigger impact on household loans than on business loans. Financial development is thus expected to reduce the cost of household credit relative to business loans and increase relative credit availability. In equilibrium, this should lead to a greater share of national output being used for consumption, instead of investment, which may depress growth by reducing capital accumulation[25].

[24]The reason is that post-securitization, the bank is no longer exposed to borrower risk, and hence has less of an interest to make sure that borrowers are of good quality (Pennacchi, 1988).

[25]This of course does not preclude that household loans by themselves could spur economic activity (for example, they may lead to higher demand for housing). It is only that if that comes at the expense of financing business activities, growth may suffer (Mills (1987) shows that the social return to housing capital is about half that to non-housing capital using U.S. data). Furthermore, the *credit composition channel* is not orthogonal to the other two channels in that it relies on securitization affecting the volume

We thus hypothesize that

Hypothesis 1: *Countries with more securitization have lower economic growth as securitization favors consumption in the economy at the expense of investment .*

From this follow two more hypotheses, relating to securitization of household and business loans separately:

Hypothesis 2: *Countries with more securitization of household loans have lower economic growth.*

Hypothesis 3: *Countries with more securitization of business loans have higher economic growth.*

3.3. Methodology and data

The data for this study has been collected from a number of sources, namely, the AB Alert and CM Alert databases, World Development Indicators (WDI), Penn World Table 8, the banking crisis database from Laeven and Valencia (2013), the World Bank regulation and supervision database, the Global Financial Development Database (GFDD), World Government Indicators and Macroprudential index from Cerutti et al. (2015)[26].

We conduct our empirical analysis by employing the following country fixed effects panel data model:[27]

$$Growth_{i,t} = \alpha_i + \beta \times Securitization_{i,t-1} + \delta' \times X_{i,t} + \theta_t + \epsilon_{i,t} \tag{3.1}$$

where the dependent variable $Growth_{i,t}$ denotes economic growth. The subindices i and t refer to country and time, respectively. $X_{i,t}$ is a set of control variables at country level[28]. We use GDP per capita growth as the main proxy for economic growth.

(or other characteristics) of either lending type. Rather, it is a general equilibrium consequence of the two micro channels.

[26] We use World Bank's WDI database as our base dataset and merge other databases starting with our securitization database - to the WDI data. Our final sample is determined by data availability, but not any other filters which may cause sample selection problems.

[27] When a Hausman test employed, fixed effects specification is selected over a random effects model confirming the importance of unobserved heterogeneity.

[28] We adopt Fisher-type panel unit root tests (specifically for unbalanced panel) with two lags in the

Alternatively, we consider growth rates of gross capital formation and growth rates of new firm density[29]. The three measures come from the WDI. In our analysis of the tradeoff between consumption and investment, we proxy the importance of consumption relative to investment with the consumption share, which is defined as the ratio of consumption to the sum of consumption and investment, constructed from Penn World Table 8. We model the relationship between the consumption share and various securitization variables similar to the growth regressions:

$$ConsumptionShare_{i,t} = \alpha_i + \beta \times Securitization_{i,t-1} + \delta' \times X_{i,t} + \theta_t + \epsilon_{i,t} \qquad (3.2)$$

Our variable of interest $Securitization_{i,t-1}$ represents total securitization issued in country i in year $t-1$. For our baseline analysis, summing up the amount of each securitization issue in a given country of a given year, we obtain a yearly aggregate amount of securitization, divided by the size of the economy, as the primary proxy for securitization intensity. In addition, we consider also the number of securitization deals normalized by the GDP as an alternative. The rationale behind this proxy is that undertaking a securitization requires a bank to adopt a new technology. Once in use, this technology is expected to be used in future circumstances. Thus it is not so much the amount of funds that in a specific securitization, but the fact that the bank has done a securitization.

We collect the data on securitization issuance from the AB Alert and CM Alert databases[30]. The two databases include all securitizations in the world that are rated by at least one major rating agency. The database distinguishes securitization issuances according to the underlying collateral. The main types are public and private asset-backed securities (ABS), mortgage-backed securities (MBS) and collateralized debt obligations (CDO), sponsored both by financial and non-financial firms. The databases, however, do not cover government-sponsored securitizations, Fannie Mae and Freddie Mac, and asset-back commercial papers (ABCP).

The two databases contain essential information on the location of collateral, types

ADF regressions with drift. The tests for securitization variables and dependent variables strongly reject the null hypothesis that all the panels contain unit roots.

[29]Gross capital formation (formerly gross domestic investment) consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Firm density refers to new firm registration per 1,000 people aged 15-64. The data on new firm density growth is available for a smaller panel since 2004 and we hence only use it in our main regressions.

[30]See Table 3.9 for securitization issuances by collateral countries since 1995.

of underlying collateral, the amount of assets securitized, and the identity of the issuer. For our purpose, we classify securitizations into two groups, depending on whether the underlying is a household loan or not[31]. Some choices had to be made since the distinction between household and other credits is not always clear-cut. Next, following Maddaloni and Peydro (2011), we create our securitization variables according to the nationality of the securitized collateral[32]. All securitization variables are lagged by one period to mitigate the concern of reverse causality. To capture possibly different effects of these two types of securitization, in some regressions we replace the total securitization measure with household and business securitization.

In order to further reduce endogeneity problems and deal with possible business cycle effects, we also employ dynamic panel regressions as a robustness check. Following the literature, we use system GMM estimation based on five-year or three-year non-overlapping averages of all variables. System GMM estimation has various advantages (Arellano and Bover, 1995; Blundell and Bond, 1998). Among others, it allows us to control for both initial GDP of countries and lagged dependent variables. Moreover, it can instrument all independent variables, including securitization measures, using their lagged levels and first-differences (the internal instruments). The validity of instruments is tested through Hansen test for overidentifying restrictions and AR(2) tests[33].

We include a set of country-level control variables, which are commonly used in the financial development literature (see, for example, Beck et al. (2014)). First, we include indicators controlling for domestic credit and stock market development, measured by domestic credit over GDP and stock traded over GDP, respectively. The credit variable controls for any direct effect of securitization on economic growth, coming through a general expansion in credit (but not taking into account changes in the composition). In addition, we include trade over GDP to measure the openness of the economy and inflation to control for macroeconomic stability. Furthermore, we control for government expenditure defined as the share of government final consumption in GDP, urbanization and education level of the country. All these macroeconomic controls come from WDI.

[31] See Table 3.10 for the final classification.

[32] We drop the deals that involve collateral from more than one country. Securitization measures are matched to variables on economic growth according to the country and the year of issuance.

[33] In the specifications with five-year averages an AR(2) test cannot be run due to the short length of the panel. When three-year averages are used instead of fiveyears, the tests are carried out and suggest that instrumentation is valid.

Since securitization activities may also affect output through increasing the likelihood of crisis, we include dummies for banking crises from Laeven and Valencia (2013) to see whether or not we capture this indirect effect. We also employ regulatory variables as additional controls (from the World Bank regulation and supervision database (Barth et al., 2013)) as a robustness check to make sure that the results are not driven by a general deregulation trend in bank activities and capital stringency accompanied by lax supervision and private monitoring. In addition, we include the country-level nonperforming loans to gross loans taken from the GFDD to capture, at least partially, the presence of the *credit quality channel*. In some robustness checks we also control for bank competition measured by Boone indicator, bank soundness measured by bank Z-score at the aggregate level, and bank credit to deposits, collected also from the GFDD. Moreover, we include institutional quality collected from the World Government Indicators (Kaufmann et al., 2011), and macroprudential policies index borrowed from Cerutti et al. (2015) in some sensitivity tests as extra controls. For details of data sources and variable definitions, please refer to Table 3.11.

Finally, we include year dummies, θ_t, to control for year specific effects. For most specifications, we estimate panel fixed effects models with standard errors clustered at the country-level, relying on within country variations to show the relationship between securitization and economic growth.

Figure 3.1 shows the trends of household and business securitization over the past two decades. Household securitization is clearly the predominant form of securitization, at least until the global financial crisis. During 2007 and 2008 both types of securitization collapsed and the large difference in issuances between both securitization types by and large disappeared.

Table 3.1 presents the summary statistics of our sample. The sample consists of 104 countries. More than half of these countries used securitizations at least once over the period of 1995 to 2012. *Securitization over GDP* has a sample mean of 0.378% and a maximum of 14.381%. In terms of types of collaterals, household securitization is the primary market segment. In particular, its sample mean, 0.242%, accounts for two-thirds of average securitization over GDP.

Table 3.2 presents the pairwise correlation matrix between main variables. First, the three measures of economic growth are positively correlated with each other, as expected.

Second, *Securitization over GDP* is negatively correlated with GDP per capita growth at the 10% significance level. Both types of securitization are negatively related to the three measures of economic growth, though the correlation is not statistically significant. Furthermore, the correlation between household and business securitization is rather limited around 0.677[34]. It is also important to note that securitization measures and consumption share are negatively correlated, albeit not significantly so. Finally, the measure of the relative importance of consumption is strongly negatively correlated with GDP, hinting at the potential importance of the composition channel.

While in our empirical analysis we exploit within country variation in securitization, it is interesting to see whether there is also a relationship between securitization and economic activity across countries. Figure 3.2 plots pre-crisis average of country-level securitization and growth rates for the OECD countries, as a rather homogenous group. We obtain a negative relationship, which is robust to the exclusion of outliers in the securitization variable.

3.4. Empirical results

Table 3.3 presents our baseline results. In column 1, we use GDP per capita growth as dependent variable and securitization over GDP as our variable of interest. The estimated coefficient for securitization over GDP is negative and significant at the 10% significance level. The economic effect of the negative association is considerable. More specifically, a one standard deviation increase in securitization over GDP (1.357) is associated with 0.18% decrease in GDP per capita growth, which is 7% of the mean ($1.357 \times 0.136/2.671$) and 4.5% of the standard deviation. While not a very large effect, the power of compounding implies an important impact on output in the medium-long run.

Most of the significant control variables have the expected sign[35]. Higher trade and urbanization increase economic growth, whereas higher inflation and government

[34]By means of comparison, in Sassi and Gasmi (2014) the correlation between household credit and enterprise credit is around 0.76.

[35]In our baseline regressions, we did not include GDP per capita in levels as we employ country fixed effects. When we include this variable as a control variable (unreported), the results are virtually the same as in our baseline regressions. The GDP per capita variable is highly insignificant suggesting country fixed-effects are capturing most of the variation there.

expenditure and banking crisis are negatively correlated with GDP per capita growth. Interestingly, domestic credit is negatively correlated with economic growth. This finding is parallel to some recent evidence analyzing similar periods on possible negative association between macroeconomy and financial developments (measured by credit supply or the importance of bank financing). Arcand et al. (2012) document non-linear and possibly negative effects of credit to GDP as the dark side of financial development and Beck et al. (2014) estimate negative coefficients for their financial intermediation variable for the 1995-2007 period, though insignificant. In a more recent article, Langfield and Pagano (2015) show that bank bias (which they measured by total bank assets over market capitalization) may have negative effects of growth performances of economies. Our analysis indicates that for fixed level of stock market development higher credit is associated with negative growth, which is effectively higher relative credit to stock market. So our negative coefficient may also be related to bank bias. Cecchetti and Kharroubi (2015) provide evidence presenting a negative relationship between growth of the financial sector and the total factor productivity (output per person employed). Maybe more interestingly, this negative relationship becomes weaker once they control for the share of the credit going to firms. Finally, one other explanation regarding the negative coefficient on domestic credit variable is provided by Loayza and Ranciere (2006), who differentiate between short- and long-term effects of financial intermediation and document the short-term effects are negative and mainly caused by financial crisis and volatility.

Columns 2 and 3 turn to the relationship between securitization and the supply side of the economy, measured by the growth rates of gross capital formation and new firm density. In each case we find a strong negative relationship. Specifically, a one standard deviation increase in securitization reduces the growth rates of gross capital formation and new firm formation by 0.74% and 2.23%. The effects are now significant at the 5% and 1% levels, respectively. This relatively stronger impact on the supply side may indicate that our composition channel is at work.

In columns 4 to 6, we turn to the separate analysis of household and business securitization. We find that household securitization is consistently negatively related to all measures of economic growth. The coefficients for household securitization are in all cases more negative than the one of total securitization. For GDP per capita growth, for example, the coefficient (significant at the 1% level) implies that a one standard deviation increase in household securitization over GDP is associated with 0.46% decrease in GDP per capita growth, which is 17% of the mean. The coefficients for business securitization are all positive except in regression 5. The significance is only marginal in regression 4, whereas there is no significance in the regressions for gross capital formation growth and new firm density growth. This evidence thus suggests that household and business loan securitizations have different implications for the macroeconomy.

In Table 3.4, we investigate through which channel(s) securitization may affect economic growth. The *credit composition channel* predicts that the growth effect of securitization comes through changing the relative importance of consumption to investment in the economy. In column 1 and 2 we use as a dependent variable the share of consumption over the sum of consumption and investment in national accounting. We find the coefficient of securitization is positive though only marginally significant at 10%. The effect is stronger for household securitization, which has a positive and significant correlation with the consumption share, suggesting household securitization increases the share of consumption. The effect for business securitization is negative but insignificant. Together with the negative relationship between consumption and growth, this provides further evidence in favor of the *credit composition channel*.

Securitization may affect economic growth through the *credit quality channel*, for example because adverse selection and moral hazard results in financing of undesirable high-risk projects. This may lower productivity, and lead to more defaults and less growth. We proxy the *credit quality channel* through the ratio of nonperforming loans to total loans at the country level, as a measure of increased bank risk and misallocation of capital, possibly due to informational problems. Columns 3 and 4 show a negative relationship of loan performance and growth. The results regarding securitization remain similar, suggesting that the composition channel operates in addition to any *credit quality channel*.

In our baseline regression, we include domestic credit as a control variable. Thus, our results are net of any effects that may come through a change in the total amount of credit in response to securitization. Consistent with this we find that in columns 5 and 6 that when domestic credit is excluded from the set of controls, the impact of securitization on growth becomes larger (in absolute terms). The securitization variable now obtains a more negative coefficient of -0.215 and is significant at the 1% level. The split-up shows that this is through a more negative impact of household securitization, the impact of business securitization weakens and is insignificant.

3.4.1. Robustness

In this section we consider several alternative specifications of the benchmark growth regressions of Table 3.3.

Table 3.5 contains various robustness checks of our results to specifications with additional control variables. In columns 1 and 2 we add extra regulatory variables to control for cross-country differences in bank regulation and supervision, which may affect securitization as well as economic growth. The motivation is that the negative association between securitization and economic growth may be driven by a general trend towards deregulation and lax supervision. Specifically, we include variables for Activity restrictions, Initial capital stringency, Supervisory powers and Private Monitoring from the bank regulation and supervision database compiled by Barth et al. (2013). The database is based on World Bank surveys on bank regulation and supervision over the period 1999-2012. The results are qualitatively unchanged. In particular, we find aggregate securitization to be negatively related to economic growth. Moreover, household securitization is negatively and significantly related to GDP per capita growth, whereas business securitization is positively related to economic growth though the effect is not statistically significant. As for the regulatory variables, only activity restrictions have significant and positive impacts on economic growth. The other regulatory variables are not significant. For brevity, we omit the estimates for the standard set of controls. In columns 3 and 4 we add population growth and the real interest rate accounting for demographic changes and the stance of monetary policy. The results are very similar to the first two regressions in the table. Both population growth and the real interest rate are negatively associated with economic growth as expected.

We control for a number of extra, country specific covariates. First, we include indicators of institutional quality, as a well-functioning legal system and institutional system is a pre-requisite of financial innovation. In addition, we consider the usage of macroprudential policies which affect the market environment and banks' incentive to undertake securitization. Following Han et al. (2015) and Gong et al. (2015) we include bank credit to deposits as the model in Han et al. (2015) suggests that banks are more likely to securitize when constrained on the funding side (indicated by a high loan to deposit ratio in Gong et al. (2015)). The results are virtually the same as our baseline regressions. Finally in columns 7 and 8 we measure of the structure of the banking system. In particular, we consider the Boone-indicator as a measure of bank competition, and the Z-score as a measure of the soundness of the financial system. None of the new control variables are significant, and the main results are robust.

Table 3.5 considers robustness of the main results by using alternative samples and securitization measures. In columns 1 to 4 of panel A, we split the sample into two groups according to median values of domestic credit to GDP variable in a given year creating developed and less developed country groups. Our results suggest that the relationship between securitization and economic growth is driven by financial developed countries, as the results in columns 1 and 2 mimic our baseline findings whereas for less developed group securitization variables are insignificant. This is unsurprising as most securitization is done in financially developed countries. Indeed, about half of countries in our sample do not securitize over the sample period. Pooling securitizing and non-securitizing countries together may hence bias the estimation of the growth effect of securitization.

In columns 5 and 6, we re-estimate our baseline model, including only countries with at least one securitization deal in the sample period. We find that securitization is negatively correlated with GDP per capita growth, though the effect is not statistically significant. When decomposing the two types of securitization, we find economic growth is negatively related to household securitization and positively related to business securitization. These results reinforce our emphasis on the importance of the distinction between household and business securitization. Finally, the U.S. has been by far the largest user of securitization in the world. To see whether this drives our results, we estimate the baseline model excluding the U.S in columns 7 and 8 and we find results similar to the baseline analysis[36].

Panel B of Table 3.6 contains regressions with alternative securitization variables. In column 1, we use the log of the number of securitization deals as alternative measures

[36]The results are also similar when we exclude top five securitizing countries (U.S., Netherlands, UK, Australia and Spain).

of securitization intensity. The results are similar, although business securitization loses its statistical significance. In columns 2 and 3, we exclude particular types of securitization from the business securitization CDOs and CLOs respectively. Column 2 shows that business loan securitization becomes much more significant once CDOs are excluded. This can be explained by the fact that CDOs are often based on synthetic transactions (that is, no actual collateral is sold) and we would hence expect a weaker relationship. Excluding CLOs (column 3), however, leads to a loss of significance for business securitization. A weaker relationship is consistent with our priors since CLOs have the ability to remove assets from the balance sheet that were previously very difficult to sell (i.e., corporate loans). Hence, they should have a large effect on the behavior of banks.

In column 4, we distinguish between securitization issued by non-financial firms and financial institutions. We find that the significant results come from securitization of financial institutions only, consistent with our argument that securitization has an effect on economic growth by affecting behavior of financial institutions. In addition, the coefficient of securitization by non-financial firms are positive and insignificant, indicating the impact of securitization is largely coming through the credit composition channel. The insignificant effect of securitization originated from the non-financial firms is also in line with Lemmon et al. (2014), which document no evidence that firms increase investment after securitization but funds from securitization are used to pay down debt.

In Table 3.7, to mitigate endogeneity concerns arising in our baseline regressions, we employ dynamic panel regressions. Specifically, we use a two-step system GMM estimator which instruments some or all independent variables or securitization variables and domestic credit variable as discussed in the previous subsection. These regressions also control for business cycle effects, as five-year or three-year non-overlapping averages of all variables are used. The system GMM regressions show that aggregate securitization has no significant effect on economic growth (in odd numbered regressions). However, in column 2, where we instrument all independent variables with first two lags, the effect of the two types of securitization individually is stronger than that in the baseline regression. The coefficient for household securitization is now -0.608, about twice (in absolute terms) the value of the baseline regression. The coefficient for corporate securitization is 1.882, more than twice its previous size, and now significant at the 1% level. These findings confirm our hypotheses that household securitization lowers economic growth but business securitization spurs real activity.

This result is robust to alternative instrumentations of the independent variables and specification of the lags used as internal instruments. In columns 3 and 4, we use only the first lag of instrumented variables to make sure that we do not overfit. The results are very similar and Hansen J statistics do not change much, reconfirming the validity of instruments. The results remains the same in columns 5 and 6 when we reduce number of instruments even further by only instrumenting securitization variables and domestic credit variable and taking other independent variables as predetermined.

In regressions 7 to 10, we use 3-year averaged variables to increase the number of observations and countries. Owing to the longer time-dimension in these regressions, AR(2) can now also be reported -on top of Hansen J test- confirming the validity of internal instruments. We further vary the number of instruments used by using the first two lags in columns 7 and 8 and only the first lags in columns 9 and 10. In those regressions, the results in terms of significance and direction of relationship are in line with earlier results, but the absolute size of the coefficients is smaller (though still larger in the baseline regressions). All in all, the system GMM results confirm that is important to distinguish the type of underlying collateral when studying the impact of securitization on growth.

The analysis so far indicates a negative relationship between securitization and economic growth. Moreover, the relationship varies depending on the type of securitization. The fact that household securitization is negatively related to growth but business related securitization is positively or not correlated with economic growth suggests differences in the macroeconomic response to securitizations. Previous research suggests that corporate credit is more productive compared to household credit, which is mostly used for consumption purposes (Beck et al., 2012). Moreover, Maddaloni and Peydro (2011) show securitization affects banks' lending behavior differentially, so that they favor consumption-related credit provision (mortgages or consumer credit), which does not directly turn into investment.

Countries with highly developed securitization markets, such as U.S. and UK, fell into recessions when the securitization market collapsed in 2008. It is thus interesting to examine whether the negative effects of securitization are due to the crisis period or whether they were already present before. In Table 3.8, we split the sample into two subsamples, the period before the crisis (1995-2006) and the crisis period (2007-2012). Column 1 shows that securitization had a negative impact on economic growth in the pre-crisis period; the effect is even stronger. The split up, in column 2, shows that the impact of household securitization is again more pronounced, and business securitization is insignificant. The result for the crisis period in column 3 shows a weak impact of aggregate securitization during the crisis. While the coefficients are not very different from the baseline analysis, the significance drops. When we split securitization as business and household securitization in column 4, only household securitization is negatively correlated to GDP per capita growth in statistically significant terms. Business securitization, on the other hand, has a positive coefficient though insignificant with a low p-value of 0.154. An explanation for the weaker results may be that the amount of securitization was much smaller in almost all of the countries during the crisis period, as well that we now look at a much shorter sample period reducing the time variance. In addition, during the crisis securitization markets did not function in an orderly fashion, making it difficult to predict how they should (or should not) affect growth.

To conclude the section, it is important to acknowledge some limitations of our analysis. Our baseline methodology is panel fixed effects regressions, which relies on strong exogeneity assumptions. Without an explicit identification strategy, the results should be interpreted as correlations rather than causal relationships. Moreover, as our data covers the period of 1995-2012, our panel regressions capture more medium-term correlations between macro variables[37]. Yet, relying only on within country variation, we avoid cross-country comparisons, which should reduce issues arising from unobserved heterogeneity. Moreover, the use of lagged securitization variables should alleviate the concern of reverse causality. The similarity of the results obtained in the dynamic panel regressions, where securitization is internally instrumented and five-year and three-year averaged variables are used, should provide additional assurance regarding endogeneity of the securitization variables and long-term relevance of our findings.

[37]The use of securitization technology intensified from late 90s onwards, not leaving us a long time horizon to analyze the long-run effects.

3.5. Conclusion

This paper has analyzed the relationship between countries' use of securitization technologies and their economic outcomes. We show that securitization is associated with lower economic activity, as proxied by growth rates of GDP per capita, capital formation and new firm density. Our results indicate that this effect is not driven by the breakdown of securitization markets during the crisis, as it is also present in the pre-crisis period.

Importantly, different types of securitizations have different effects. Whereas securitization of loans to households is negatively related to economic activity, securitization of business loans has a weak positive effect on the economy. The findings are consistent with the *credit composition channel*, by which securitization of non-business loans leads to an increase in the share of credits flowing to households, as the cost of firm financing. While this may spur demand in the short run, it will hamper investment and lead to lower growth.

Our results carry clear policy messages. Securitization may not only have effects on the parties immediately involved in the securitization process, but also for the wider economy. Most importantly, the results suggest that the impact of securitization depends on the underlying type of collateral. While securitization of business loans may encourage investment and spur economic activity, securitization of consumer loans may at the aggregate divert resources away from productive purposes. The ongoing debate on whether to revive securitization should thus put a focus on which part of the securitization market to stimulate. Policy makers clearly recognize the importance of fostering "high-quality" securitization, that is, securitizations that are transparent and include collateral of low risk borrowers. Our analysis suggests that the authorities should not only care about the securitization quality, but also whether the collateral is in the form of household or business loans. If the objective is to stimulate growth and investment, the focus should be on the latter.

Table 3.1: Cross-country summary statistics

	No. of obs.	Mean	Std. Dev.	Min	Max
GDP per capita growth	1238	2.671	4.08	-17.545	38.057
Gross Capital Formation Growth	1126	5.218	15.144	-57.713	106.35
New Firm Density Growth	440	6.266	19.303	-45.455	133.333
Consumption share	1218	77.338	9.007	27.262	97.672
Securitization over GDP	1238	0.378	1.357	0	14.381
Household securitization over GDP	1238	0.242	0.992	0	9.956
Business securitization over GDP	1238	0.136	0.467	0	5.173
Ln(Securitization deals)	1238	0.654	1.312	0	8.005
Ln(Household securitization deals)	1238	0.46	1.128	0	7.394
Ln(Business securitization deals)	1238	0.476	1.067	0	7.231
Business securitization net of CDO over GDP	1238	0.095	0.313	0	3.442
Business securitization net of CLO over GDP	1238	0.122	0.428	0	4.74
Securitization by financial firms	1238	0.348	1.308	0	14.238
Securitization by nonfinancial firms	1238	0.04	0.164	0	2.513
Domestic credit to private sector	1238	70.362	53.804	3.829	319.461
Stocks traded over GDP	1238	36.043	68.969	0	741.584
Trade over GDP	1238	90.427	52.235	18.756	448.306
Inflation	1238	7.519	33.838	-4.863	1058.374
Government expenditure	1238	16.65	5.001	4.506	30.504
Urbanization	1238	64.34	20.01	10.072	100
Education	1238	87.191	23.702	16.477	160.619
Population growth	1233	1.072	1.504	-3.821	17.483
Real interest rate	1028	7.013	10.559	-71.205	97.474
Banking Crisis	1238	0.124	0.33	0	1
Activity restrictions	1043	7.136	2.052	3	12
Initial capital stringency	1060	2.136	0.794	0	3
Supervisory powers	870	11.04	2.408	4	16
Private Monitoring	993	8.182	1.393	4	11
Institutional quality	676	0.374	0.85	-1.177	1.986
Macroprudential index	676	1.72	1.599	0	8
Bank credit to deposits	676	108.618	47.056	30.63	364.67
Bank competition	1070	-0.059	0.403	-4.84	4.38
Bank soundness	1082	15.072	10.78	-7.31	65.36
NPL to gross loans	870	7.106	7.812	0.1	48.6

Table 3.2: Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) GDP per capita growth	1						
(2) Gross Capital Formation Growth	0.598***	1					
(3) New Firm Density Growth	0.368***	0.365***	1				
(4) Securitization over GDP	-0.048*	-0.025	-0.028	1			
(5) Household securitization over GDP	-0.046	-0.026	-0.015	0.967***	1		
(6) Business securitization over GDP	-0.041	-0.019	-0.047	0.843***	0.677***	1	
(7) Consumption share	-0.078***	-0.109***	-0.047	-0.030	-0.022	-0.042	1

Table 3.3: Securitization and the real economy

GDP per capita growth is the rate of real per capita GDP growth. New firm density growth is the growth rate of new business entry density, which is the number of newly registered limited liability corporations per calendar year, normalized by working age population. Gross capital formation consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Securitization over GDP is total securitization amount over GDP. Household securitization over GDP is the total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP. Business securitization over GDP is the total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP. Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations. Stocks traded over GDP refers to the total value of shares traded during the period over GDP. Trade over GDP is total trade over GDP. Inflation is the rate of change in consumer price indices. Government expenditure is the general government final consumption expenditure (% of GDP). Urbanization is the urban population (% of total population). Education is the gross secondary education enrollment ratio. Banking crisis is a dummy variable that equals 1 if the country is in a banking crisis. All securitization related variables are lagged one period. Country and year fixed effects are included in each specification. Standard errors are clustered at the country-level. Robust P-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	GDP per capita growth (1)	Gross Capital Formation Growth (2)	New Firm Density Growth (3)	GDP per capita growth (4)	Gross Capital Formation Growth (5)	New Firm Density Growth (6)
Securitization over GDP	-0.136*	-0.542**	-1.642***			
	(0.062)	(0.045)	(0.006)			
Household securitization over GDP				-0.344***	-0.653**	-2.410***
				(0.000)	(0.039)	(0.000)
Business securitization over GDP				0.371*	-0.250	0.165
				(0.086)	(0.815)	(0.911)
Domestic credit to private sector	-0.027***	-0.083**	0.002	-0.027***	-0.083**	-0.001
	(0.003)	(0.026)	(0.964)	(0.002)	(0.026)	(0.986)
Stocks traded over GDP	0.002	0.010	0.039*	0.001	0.010	0.038*
	(0.661)	(0.325)	(0.060)	(0.705)	(0.341)	(0.063)
Trade over GDP	0.032***	0.130**	0.090	0.031***	0.130**	0.091
	(0.006)	(0.015)	(0.424)	(0.006)	(0.015)	(0.412)
Inflation	-0.013*	-0.004	-0.728*	-0.013*	-0.004	-0.728*
	(0.073)	(0.572)	(0.067)	(0.074)	(0.574)	(0.067)
Government expenditure	-0.257***	-0.155	-2.600***	-0.258***	-0.156	-2.587***
	(0.000)	(0.778)	(0.001)	(0.000)	(0.777)	(0.001)
Urbanization	0.236***	0.925***	1.453	0.239***	0.926***	1.471
	(0.005)	(0.006)	(0.322)	(0.005)	(0.006)	(0.318)
Education	-0.000	-0.108**	-0.389	-0.001	-0.108**	-0.387
	(0.980)	(0.027)	(0.201)	(0.928)	(0.027)	(0.205)
Banking Crisis	-1.610***	-4.116**	3.681	-1.635***	-4.130**	3.679
	(0.002)	(0.019)	(0.200)	(0.002)	(0.018)	(0.206)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,238	1,131	442	1,238	1,131	442
R-squared	0.333	0.228	0.274	0.335	0.228	0.275
Number of countries	104	96	78	104	96	78

Table 3.4: Securitization channels

Consumption share is total consumption over the sum of investment and consumption. Securitization over GDP is total securitization amount over GDP. Household securitization over GDP is the total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP. Business securitization over GDP is the total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP. NPL to gross loans is aggregate bank non-performing loans to gross loans in percentages. Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations. Stocks traded over GDP refers to the total value of shares traded during the period over GDP. Trade over GDP is total trade over GDP. Inflation is the rate of change in consumer price indices. Government expenditure is the general government final consumption expenditure (% of GDP). Urbanization is the urban population (% of total population). Education is the gross secondary education enrollment ratio. Banking crisis is a dummy variable that equals 1 if the country is in a banking crisis. Described control variables are included in the regressions but not reported in the table. Government expenditure is not included in regressions 1 and 2. All securitization related variables are lagged one period. Country and year fixed effects are included in each specification. Standard errors are clustered at the country-level and P-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	Consumption share		GDP per capita growth			
Channels	Credit composition channel		Credit quality channel		Credit volume channel	
	(1)	(2)	(3)	(4)	(5)	(6)
Securitization over GDP	0.204*		-0.118		-0.215***	
	(0.062)		(0.125)		(0.002)	
Household securitization over GDP		0.336**		-0.328***		-0.408***
		(0.027)		(0.001)		(0.000)
Business securitization over GDP		-0.120		0.428**		0.253
		(0.714)		(0.030)		(0.202)
NPL to Gross Loans			-0.121***	-0.120***		
			(0.002)	(0.002)		
Domestic credit to private sector	-0.025**	-0.025**	-0.030***	-0.030***		
	(0.038)	(0.041)	(0.003)	(0.003)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,233	1,233	870	870	1,261	1,261
R-squared	0.201	0.201	0.429	0.431	0.319	0.321
Number of wbencode	103	103	85	85	104	104

Table 3.5: Additional control variables

GDP per capita growth is the rate of real per capita GDP growth. Securitization over GDP is total securitization amount over GDP. Household securitization over GDP is the total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP. Business securitization over GDP is the total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP. ln(Securitization deals) is log of number of securitization issuances plus one. ln(Household [Business] Securitization deals) is log of number of household [business] related securitization issuances plus one. Activity restriction captures overall restrictions on banking activities and Initial capital stringency shows how stringent capital rules are when a bank is initially capitalized. Supervisory powers indicates how strong the supervisory authorities are and Private monitoring captures the effectiveness of private monitoring of firms. Population growth (annual %) is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage. Real interest rate is lending interest rate adjusted for inflation as measured by the GDP deflator. Institutional quality is an aggregate governance indicator proxying institutional quality in a country. Macroprudential index is an index measuring different macroprudential policies in a country. Bank credit to deposits is bank credit to bank deposits (%). Bank competition is measured by Boone indicator which is a measure of degree of competition based on profit-efficiency in the banking market. It is calculated as the elasticity of profits to marginal costs. An increase in the Boone indicator implies a deterioration of the competitive conduct of financial intermediaries. Bank soundness is measured by bank Z-score which captures the probability of default of a country's commercial banking system. We also include the following control variables: Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations. Stocks traded over GDP refers to the total value of shares traded during the period over GDP. Trade over GDP is total trade over GDP. Inflation is the rate of change in consumer price indices. Government expenditure is the general government final consumption expenditure (% of GDP). Urbanization is the urban population (% of total population). Education is the gross secondary education enrollment ratio. Banking crisis is a dummy variable that equals 1 if the country is in a banking crisis. Described control variables are included in the regressions but not reported in the table. In rest of the regressions, country and year fixed effects are included in each specification, all securitization related variables are lagged one period and standard errors are clustered at the country-level. P-values are reported in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1.

	GDP per capita growth							
	Regulation		Population growth & real interest rate		Institutional quality & macroprudential policies		Bank structure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Securitization	-0.156*		-0.152*		-0.138**		-0.151*	
	(0.054)		(0.052)		(0.040)		(0.051)	
Household securitization		-0.358***		-0.347**		-0.205**		-0.326***
		(0.003)		(0.014)		(0.039)		(0.001)
Business securitization		0.285		0.258		0.043		0.283
		(0.232)		(0.365)		(0.824)		(0.205)
Activity restrictions	0.225*	0.219*						
	(0.074)	(0.082)						
Initial capital stringency	0.415	0.388						
	(0.101)	(0.124)						
Supervisory powers	0.099	0.102						
	(0.132)	(0.122)						
Private Monitoring	0.101	0.102						
	(0.478)	(0.467)						
Population growth			-0.963***	-0.963***				
			(0.000)	(0.000)				
Real interest rate			-0.055*	-0.055*				
			(0.072)	(0.072)				
Institutional quality					1.982	1.974		
					(0.159)	(0.161)		
Macroprudential index					-0.263	-0.260		
					(0.383)	(0.389)		
Bank credit to deposits					-0.058***	-0.058***		
					(0.000)	(0.000)		
Bank competition							-0.131	-0.124
							(0.865)	(0.870)
Bank soundness							-0.012	-0.012
							(0.617)	(0.631)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	828	828	1024	1024	676	676	1009	1009
R-sq	0.340	0.341	0.358	0.359	0.472	0.472	0.389	0.390
Number of countries	90	90	98	98	82	82	100	100

Table 3.6: Alternative samples and securitization measures

GDP per capita growth is the rate of real per capita GDP growth. Securitization over GDP is total securitization amount over GDP. Household securitization over GDP is the total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP. Business securitization over GDP is the total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP. ln(Household [Business] Securitization deals) is log of number of household [business] related securitization issuances plus one. Securitization by [non-]financial firms is securitization issued by [non-]financial firms. We also include the following control variables: Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations. Stocks traded over GDP refers to the total value of shares traded during the period over GDP. Trade over GDP is total trade over GDP. Inflation is the rate of change in consumer price indices. Government expenditure is the general government final consumption expenditure (% of GDP). Urbanization is the urban population (% of total population). Education is the gross secondary education enrollment ratio. Banking crisis is a dummy variable that equals 1 if the country is in a banking crisis. Described control variables are included in the regressions but not reported in the table. In Panel A, regressions 1 to 4 the sample is split by yearly median value of domestic credit as developed and less developed countries. In regressions 5 and 6 only countries with any securitization activity is included, and in regressions 7 and 8, the U.S. is excluded. In Panel B, in regressions 2 and 3 CDO, CLO are excluded from the business securitization, respectively. Country and year fixed effects are included in each specification, all securitization related variables are lagged one period and standard errors are clustered at the country-level. P-values are reported in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1.

Panel A: Alternative samples	GDP per capita growth							
	Developed		Less Developed		Only securitizing countries		Excluding the U.S.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Securitization	-0.131*		-0.205		-0.051		-0.130	
	(0.063)		(0.764)		(0.412)		(0.146)	
Household securitization		-0.314***		-14.085		-0.235***		-0.360***
		(0.000)		(0.110)		(0.002)		(0.001)
Business securitization		0.355**		0.077		0.406**		0.417*
		(0.049)		(0.918)		(0.048)		(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	619	619	619	619	690	690	1223	1223
R-sq	0.482	0.485	0.284	0.291	0.469	0.472	0.332	0.334
Number of countries	65	65	70	70	54	54	103	103

Panel B: Alternative measures of securitization	GDP per capita growth			
	Ln(Number of issuances)	Non-CDO	Non-CLO	Non-financials
	(1)	(2)	(3)	(4)
Household securitization	-0.655***	-0.351***	-0.315***	
	(0.002)	(0.000)	(0.001)	
Business securitization	0.164	0.674***	0.275	
	(0.377)	(0.006)	(0.260)	
Securitization by financial firms				-0.158**
				(0.034)
Securitization by non-financial firms				0.442
				(0.302)
Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Number of observations	1238	1238	1238	1238
R-sq	0.337	0.336	0.335	0.334
Number of countries	104	104	104	104

Table 3.7: Dynamic panel regressions

GDP per capita growth is the rate of real per capita GDP growth. Securitization over GDP is total securitization amount over GDP. Household securitization over GDP is the total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP. Business securitization over GDP is the total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP. We also include the following control variables: Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations. Stocks traded over GDP refers to the total value of shares traded during the period over GDP. Trade over GDP is total trade over GDP. Inflation is the rate of change in consumer price indices. Government expenditure is the general government final consumption expenditure (% of GDP). Urbanization is the urban population (% of total population). Education is the gross secondary education enrollment ratio. Banking crisis is a dummy variable that equals 1 if the country is in a banking crisis. Initial GDP per capita is the GDP per capita in 1995. Described control variables are included in the regressions but not reported in the table. In dynamic panel regressions 1 to 6 [7 to 10] -two-step system GMM estimation- 5-year [3-year] non-overlapping averages for all variables are used, together with period fixed effects. In regression 1 to 4 all independent variables are instrumented, in all other regressions only securitization variables and domestic credit variable are instrumented. P-values are reported in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1.

	GDP per capita growth									
	5 year averages						3 year averages			
	All variables instrumented				Only securitization and domestic credit instrumented					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Securitization	0.026		-0.096		-0.098		-0.015		-0.021	
	(0.862)		(0.594)		(0.495)		(0.907)		(0.877)	
Household securitization		-0.608**		-0.612**		-0.758**		-0.416**		-0.483*
		(0.011)		(0.042)		(0.019)		(0.033)		(0.054)
Business securitization		1.882***		1.624**		1.676**		1.118**		1.216*
		(0.007)		(0.050)		(0.029)		(0.030)		(0.058)
Lagged GDP per capita growth	0.147	0.173*	0.077	0.094	0.307**	0.286**	0.206**	0.218**	0.234**	0.223**
	(0.159)	(0.062)	(0.451)	(0.399)	(0.042)	(0.019)	(0.042)	(0.011)	(0.025)	(0.013)
Initial GDP per capita	-0.152	-0.288	-0.079	-0.121	-0.113	-0.154	0.076	0.101	0.070	0.050
	(0.585)	(0.190)	(0.663)	(0.675)	(0.631)	(0.501)	(0.667)	(0.591)	(0.729)	(0.787)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	118	118	118	118	118	118	313	313	313	313
Number of countries	77	77	77	77	77	77	92	92	92	92
Number of Instruments	54	58	47	51	28	31	58	72	45	55
Lags used for instrumentation	2	2	1	1			2	2	1	1
AR2 test p-values							0.452	0.514	0.655	0.573
Hansen J-test (p-value)	0.379	0.493	0.539	0.458	0.112	0.301	0.470	0.544	0.220	0.260

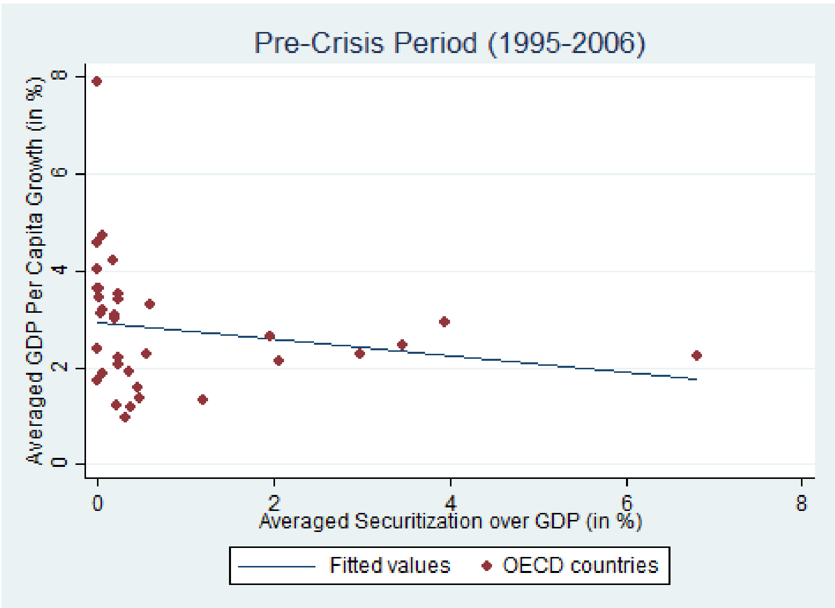
Table 3.8: Securitization before and after the global financial crisis

GDP per capita growth is the rate of real per capita GDP growth. Securitization over GDP is total securitization amount over GDP. Household securitization over GDP is the total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP. Business securitization over GDP is the total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP. Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations. Stocks traded over GDP refers to the total value of shares traded during the period over GDP. Trade over GDP is total trade over GDP. Inflation is the rate of change in consumer price indices. Government expenditure is the general government final consumption expenditure (% of GDP). Urbanization is the urban population (% of total population). Education is the gross secondary education enrollment ratio. Banking crisis is a dummy variable that equals 1 if the country is in a banking crisis. In regressions 1 and 2, observations from years before 2007 and in regressions 3 and 4 from year after 2006 are used. All securitization related variables are lagged one period. Country and year fixed effects are included in each specification. Standard errors are clustered at the country-level and P-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	GDP per capita growth			
Sample periods	1995–2006		2007–2012	
	(1)	(2)	(3)	(4)
Securitization over GDP	-0.312**		-0.126	
	(0.012)		(0.170)	
Household securitization over GDP		-0.411**		-0.328**
		(0.017)		(0.024)
Business securitization over GDP		-0.049		0.387
		(0.893)		(0.154)
Domestic credit to private sector	-0.023***	-0.023***	-0.022	-0.026
	(0.008)	(0.008)	(0.351)	(0.257)
Stocks traded over GDP	0.015**	0.015**	0.003	0.002
	(0.020)	(0.022)	(0.521)	(0.680)
Trade over GDP	0.032**	0.031**	0.079**	0.080**
	(0.036)	(0.039)	(0.043)	(0.040)
Inflation	-0.014*	-0.014*	0.034	0.034
	(0.081)	(0.081)	(0.679)	(0.678)
Government expenditure	-0.283***	-0.284***	-0.679**	-0.676**
	(0.001)	(0.001)	(0.013)	(0.014)
Urbanization	0.086	0.088	0.825**	0.842**
	(0.441)	(0.432)	(0.049)	(0.044)
Education	0.011	0.011	-0.043	-0.320
	(0.519)	(0.549)	(0.499)	(0.281)
Banking Crisis	-2.034***	-2.033***	-8.282**	-0.915
	(0.009)	(0.009)	(0.010)	(0.776)
Year Dummies	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	837	837	361	361
R-squared	0.245	0.245	0.110	0.466
Number of wbencode	98	98	89	87

Figure 3.1: Composition of securitization: household related and business related securitization

Figure 3.2: Economic growth and securitization intensity before the global financial crisis



Notes: The data is averaged over the period of 1995–2006 for the OECD countries. Graphs without outliers of the full period (1005-2012) look very similar.

APPENDIX

Table 3.9: Sample countries and securitization activities

The distribution of total amount of securitization issuances in millions of U.S. dollars across countries over time.

Country	1995-2000	2001-2006	2007-2012	Country	1995-2000	2001-2006	2007-2012	Country	1995-2000	2001-2006	2007-2012
ARE	0	350	1599	ESP	20506	210705	178215	NOR	0	0	4370
ARG	2788	334	150	FIN	2540	997	637	NZL	1042	942	941
AUS	39912	181385	138601	FRA	44881	43744	21854	OMN	0	925	0
AUT	650	5785	4292	GBR	126893	827100	563392	PAK	250	0	0
BEL	5497	7596	12924	GRC	1100	13609	7198	PAN	186	150	1240
BHR	0	334	0	GTM	0	0	480	PER	550	1903	4094
BIH	0	0	110	HKG	2606	2122	2207	PHL	75	0	0
BLZ	0	45	0	IDN	886	0	9	POL	809	625	342
BRA	4093	6624	7977	IRL	0	711	29449	PRT	2400	38414	23143
CAN	17168	41527	43800	ISL	0	384	0	RUS	53	5219	6318
CHE	5943	7160	1515	ISR	0	37	0	SGP	225	4319	2345
CHL	150	40	0	ITA	20506	193268	88050	SLV	110	0	0
CHN	2117	403	0	JAM	125	100	50	SWE	2040	4346	4973
COL	887	206	0	JPN	44515	119289	160690	THA	753	664	421
CRI	0	63	0	KAZ	0	700	1400	TTO	0	150	0
CZE	0	218	0	KOR	3540	10697	6469	TUR	2489	9346	6463
DEU	25541	124317	162988	LUX	137	0	661	UKR	0	0	281
DNK	223	1132	21797	MEX	11780	1516	8105	USA	2189615	7181403	2773118
DOM	22	0	0	MYS	81	1344	315	VEN	4120	0	0
EGY	0	1554	0	NLD	21391	177768	159369	ZAF	361	7634	7355

Table 3.10: Types of securitization

Household related:	**Business related:**	
AL Auto Leases	AC Aircraft-lease receivables	MZ Mutual fund (12b-1) fees
AS Auto loans (subprime)	AF Auto-fleet leases	NM Net interest margin
AU Auto loans (prime)	AK Airline-ticket receivables	NR Natural resources
BO Boat loans	BZ Bank loans (CLOs)	PF Project finance
CN Consumer loans, unsecured	CA Catastrophic risk	RN Rent receipts
CR Credit cards	CB Collateralized debt obligation	RO Royalties
HE Home-equity loans	CK Credit risk*	RV Recreational-vehicle loans
HI Home-improvement loans	CM Commercial MBS	RY Remittances (by immigrants)
HL Home-equity lines of credit	CM Commercial MBS (non-performing)	SA Servicer advance receivables
MH Manufactured housing loans	DR Delinquent receivables*	SB Small-business loans
MI Non-U.S. residential loans	EL Equipment loans	SC Small-business loans (Non-U.S.)
MO Motorcycle loans	EQ Equipment leases	SE Legal settlements
MR Reverse mortgages	EX Export receivables. (Ex-Im Guarantee)	TL Tax liens
NE High-LTV (”no-equity”) loans	EZ Export receivables (Other)	TM Timeshare loans
NP Non-performing mortgages	FE Miscellaneous*	TO Toll-road receivables
RM Residential mortgages (includes Alt-A)	FF Franchise fees	TP Transportation
SM Subprime mortgages	FL Franchise loans	TR Trade receivables
ST Student loans	FP Floorplan loans	TU Truck loans
	GC Guaranteed investment contract	UT Utility receivables
	HC Healthcare receivables*	VI Viatical settlements
	IN Insurance-premium loans	WB Whole-business
	MU Municipal leases	WE Weather

Notes: Collateral codes are taken from the AB Alert and CM Alert databases. * indicates rather ambiguous types of collateral, the exclusion of which does not affect our results.

Table 3.11: Data descriptions and sources
* See the appendix for the details of underlying collaterals. All securitization variables are lagged one period.

Variables	Descriptions	Sources
GDP per capita growth	Real GDP per capita growth in percentages.	WDI
Gross capital formation	Gross capital formation (formerly gross domestic investment) consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories.	WDI
New firm density growth	The new business entry density, which is the number of newly registered limited liability corporations per calendar year, normalized by working age population.	WDI
Consumption share	Total consumption over the sum of investment and consumption.	Penn World Table 8
Securitization over GDP	Total amount of all rated asset-backed issues, mortgage-backed issues, CDO's and securities collateralized by commercial and multi-family properties over GDP. Excludes Fannie Mae and Freddie Mac issues, municipality issues and commercial papers*.	AB and CM Alert
Household securitization over GDP	Total amount of securitization collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.) over GDP*.	AB and CM Alert
Business securitization over GDP	Total amount of securitization collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.) over GDP*.	AB and CM Alert
Ln(Securitization deals)	Ln(1+ total number of securitization deals)	AB and CM Alert
Ln(Household securitization deals)	Ln(1+ total number of securitization deals collateralized by household related underlying assets (such as consumer loans, credit cards, mortgages etc.))*.	AB and CM Alert
Ln(Business securitization deals)	Ln(1+ total number of securitization deals collateralized by business related underlying assets (such as commercial mortgages, small business loans, bank loans etc.))*.	AB and CM Alert
Business securitization net of CDO over GDP	Total amount of business securitization net of collateralized debt obligations (CDOs) over GDP.	AB and CM Alert

Business securitization net of CLO over GDP	Total amount of business securitization net of collateralized loan obligations (CLOs) over GDP.	AB and CM Alert
Securitization by financial firms	Total amount of securitization issued by financial firms over GDP.	AB and CM Alert
Securitization by nonfinancial firms	Total amount of securitization issued by non-financial firms over GDP.	AB and CM Alert
Domestic credit to private sector	Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment.	WDI
Stocks traded over GDP	Stocks traded refers to the total value of shares traded during the period. This indicator complements the market capitalization ratio by showing whether market size is matched by trading.	WDI
Trade over GDP	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product.	WDI
Inflation	Inflation, consumer prices (annual %).	WDI
Government expenditure	General government final consumption expenditure (% of GDP).	WDI
Urbanization	Urban population (% of total).	WDI
Education	Gross secondary education enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown.	WDI
Population growth	Population growth (annual %) is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage.	WDI
Real interest rate	Lending interest rate adjusted for inflation as measured by the GDP deflator.	WDI
Banking crisis	Dummy variable equals 1 if the country suffers from systemic banking crisis.	Laeven and Valencia (2013)
Activity restriction	Overall Restrictions on Banking Activities regarding insurance, securities and real estate activities of banks. From 3 to 12. Higher values indicate more restrictive.	WB surveys on bank regulation (Barth et al., 2013)

Initial capital stringency	Whether certain funds may be used to initially capitalize a bank and whether they are officially. From 0 to 3. Higher values indicate greater stringency.	WB surveys on bank regulation (Barth et al., 2013)
Supervisory powers	Whether the supervisory authorities have the authority to take specific actions to prevent and correct problems. From 4 to 16. Higher values indicate stronger supervision.	WB surveys on bank regulation (Barth et al., 2013)
Private monitoring	Whether the supervisory authorities have the authority to take specific actions to prevent and correct problems. From 4 to 11. Higher values indicate stronger monitoring.	WB surveys on bank regulation (Barth et al., 2013)
Macroprudential index	An index proxying the usage of macroprudentail policies (such as loan-to-value ratios, concentration limits etc.). Higher values indicate higher usage of macroprudential policies.	Cerutti et al. (2015)
Bank credit to deposits	Bank credit to bank deposits (%).	GFDD
Bank competition	Boone indicator. A measure of degree of competition based on profit-efficiency in the banking market. It is calculated as the elasticity of profits to marginal costs. An increase in the Boone indicator implies a deterioration of the competitive conduct of financial intermediaries.	GFDD
Bank soundness	Bank Z-score which captures the probability of default of a country's commercial banking system.	GFDD
NPL to Gross Loans	Bank non-performing loans to gross loans at the country-level (%).	GFDD
Institutional quality	An aggregate governance indicator (including different dimensions of governance such as rule of law, control of corruption etc.) proxying institutional quality (see Kaufmann et al. (2011)). Higher values indicate higher institutional quality.	World Government Indicators

Chapter 4

Systemic risk-taking at banks: Evidence from the pricing of syndicated loans

4.1. Introduction

Since the recent financial crisis is essentially a systemic crisis in which a large fraction of banking sectors failed simultaneously and incurred huge economic and social costs, systemic risk-taking at banks has become an important agenda for both policymakers and researchers. This paper aims to provide empirical evidence of banks' systemic risk-taking in the market of syndicated lending. Specifically, we document systemic risk-taking from the pricing of syndicated loan contracts. More importantly, we relate the incentive of banks' risk-taking to the "too-many-to-fail" bailout policy.

Banks may take systemic risk due to the fact that bank failure resolutions of regulatory agencies depend on whether the problem arises due to idiosyncratic or aggregate reasons (Acharya and Torulmazer, 2007). According to a review of the history of bank failures and resolution by Hoggarth, Reidhill and Sinclair (2004), in case of individual bank failure, regulators usually stand alone and seek private sector resolutions, such as merger and acquisition or liquidation. On the contrary, regulators often intervene in systemic crises in the forms of liquidity support, blanket guarantees or capital injections, when the cost of discontinuation of investment, fire sales and contagion outweighs the cost of bailout. The bailout in joint bank failures, or "too-many-to-fail" summarized in Acharya and Torulmazer (2007), may distort banks' incentives ex-ante when banks are aware of safety in similarity. Therefore, banks have strong incentives to make any problem a system-wide one and therefore maximize the likelihood of joint failure and hence collective bailout. A simple way for banks to take systemic risk is to expand aggregate exposure to the state of the economy. Essentially, banks can build up systemic risk at the balance sheet by investing in the aggregate risk in assets.

How can we learn about systemic risk-taking from the pricing of loans? In absence of systemic risk-taking, the compensation required for aggregate risk should be higher than (or at least as high as) the compensation for idiosyncratic risk[38]. This is because idiosyncratic risk is diversifiable (imperfectly though for banks, in contrast to stock investors). Hence lending rates for aggregate exposure should be higher than for idiosyncratic exposures. Suppose now that a "too-many-to-fail" bailout policy is in place, in which the regulator bails out banks if they fail jointly (Acharya and Yorulmazer, 2007). This provides incentives for banks to take on risks that make them more correlated. Taking on aggregate risk is the easiest way to become correlated as most banks can easily increase exposure to aggregate risk (by contrast, herding on for example a specific exposure, like a certain region, will be more difficult for banks)[39]. Thus, the "too-many-to-fail" guarantee provides a rationale for banks to charge lower lending rates for taking on aggregate risk relative to idiosyncratic risk. Evidence of lower lending rates for aggregate risk, after properly accounting for other factors, is thus evidence for systemic risk-taking at banks.

We empirically examine this question using a sample of the U.S. syndicated loans from Dealscan over the period 1988 to 2011. Adopting equity volatility of the borrower to proxy for the aggregate and idiosyncratic risks of the loan contract, we find that loan spreads are positively associated with borrowers' idiosyncratic risk whereas negatively associated with aggregate risk, controlling for borrower, loan and lender specific factors as well as year dummies. A one standard deviation increase in idiosyncratic risk raises the loan spread by 28 basis points, whereas a one standard deviation rise in aggregate risk lowers the lending rate by 5 basis points. Although the spread undercut on aggregate risk is not economically significant, the results imply that bank do not charge risk premium but rather offer lending rate discount to aggregate risk, which to some extent reveals the expected magnitude of the bailout subsidy a bank can obtain. Overall, the underpricing

[38]One reason to look at loan pricing is because there is a clear benchmark for different treatments of idiosyncratic and aggregate risks. For instance, CAPM is a typical pricing benchmark based on portfolio theory in absence of any distortion.

[39]We are fully aware of the distinction between the two terms, systematic risk and systemic risk, as classified in Hansen (2012). Systematic risk is the aggregate risk which cannot be diversified away. Systemic risk refers to the risk imposed by interbank correlation that may bring down the entire banking industry. Still, the two concepts are intrinsically linked in our framework.

of aggregate risk relative to idiosyncratic risk can be taken as evidence of systemic risk-taking at banks. This pricing pattern is robust to risk measures of equity volatility estimated from CAPM regression and Fama-French three-factor regression. In addition, we show that such pricing patterns are not driven by borrowers' or lenders' unobserved heterogeneity as the results continue to hold when firm fixed effects or bank fixed effects are included.

Public guarantees in systemic crises apply largely to banks[40]. Non-bank lenders hence constitute an important control group. Consistent with systemic risk-taking driving the results for the bank sample, we find that for the sample of non-bank lenders, lending rates are higher for aggregate risk consistent with the traditional portfolio theory. This provides strong evidence that results in the bank sample are driven by systemic risk-taking incentives. In addition, we address the concern of incomparable clients of banks and non-banks by applying the propensity score matching technique. Consistently, we find different pricing patterns in a matched sample of loans borrowed by similar firms but issued by banks and non-bank lenders.

An important motive for systemic risk-taking is the "too-many-to-fail" policy, which provides lowly correlated banks a rationale to become correlated in order to benefit from the bailout subsidy (Acharya and Yorulmazer, 2007). Consistent with this, interacting borrowers' aggregate and idiosyncratic risks with a market-based interbank correlation dummy, we find that less correlated banks charge lower spreads on aggregate risk relative to more correlated banks. When splitting the sample into two subsamples of highly and lowly correlated bank, we find only lowly correlated banks offer interest rate discounts on aggregate risk. The test of the impact of interbank correlations on loan pricing restricts the sample to publicly traded banks. To test the "too-many-to-fail" effect in a more general sample, we rely on bank accounting variables and test whether small banks are more aggressive in systemic risk-taking, a proposition in Acharya and Yorulmazer (2007). Interacting a bank size dummy with borrowers' aggregate and idiosyncratic risks, we find that smaller banks charge lower spreads on aggregate risk relative to larger banks, in

[40] Although large non-bank firms such as AIG, General Motors and Chrysler were also bailed out in the recent financial crisis, they accounted for a very small fraction of bailout recipients of the failed financial institutions. Therefore, the likelihood of being rescued by the public guarantee remains low for non-bank lenders. For the list of bailout recipients, please visit ProPublica http://projects.propublica.org/bailout/list. To track the list of bailout bank in the Capital Purchase Program, please visit http://money.cnn.com/news/specials/storysupplement/bankbailout/

line with the prediction of "too-many-to-fail" story. It is notably that the large banks require more compensation for both aggregate and idiosyncratic risks, different from the standard "too-big-to-fail" story.

This paper contributes to three strands of literature. First, in spite of fruitful studies on bank risk-taking in general (see Laeven and Levine, 2009; Keeley, 1990; Gropp, Gruendl and Guettler, 2013; Gropp, Hakenes and Schnabel, 2010; DeYoung, Peng and Yan, 2013; Altunbas, Gambacorta and Marqués-Ibáñez, 2010), the specific research on bank systemic risk-taking has been concentrated on theoretical models as it is challenging to empirically identify systemic risk-taking behaviors in the real world. This paper adds new empirical evidence of bank systemic risk-taking from the syndicated loan market. We illustrate systemic risk-taking from the underpricing of aggregate risk of loans, in contrast to Cai, Saunders and Steffen (2011) who document bank systemic risk-taking based on the interconnectedness of banks which is directly constructed from syndicated loan portfolios.

More broadly, this paper is related to the discussion of the impact of government guarantees on bank risk-taking. Banking theory suggests two opposite effects coexist. On the one hand, government support augments a bank's charter value and therefore discourages risk-taking (Keeley, 1990). On the other hand, public support mitigates market discipline as the incentive for investors to monitor the risk-shifting at the bank is reduced (Merton, 1977; Dam and Koetter, 2012; Gropp, Gruendl and Guettler, 2013; Brandao-Marques, Correa and Sapriza, 2012). Empirical studies present, however, mixed results, indicating that the net effect of government guarantees on risk-taking is ambiguous and depends on which effect dominates (Cordella and Yeyati, 2003). This paper adds new empirical evidence that the moral hazard effect of the government support dominates as banks protected by the "too-many-to-fail" guarantee tend to take systemic risk aggressively. This is related to the finding that suppoted banks charge lower loan spreads relative to a market benchmark by Gadanecz, Tsatsaronis, and Altunbas (2012).

Last, though the "too-many-to-fail" problem has drawn extensive attention in banking regulation especially since the recent financial crisis (Vives, 2011), empirical work testing this theory remains scarce. To the best of our knowledge, our paper is the first which unveils evidence of the ex-ante effect of "too-many-to-fail" that banks may intentionally extract bailout subsidies by taking systemic risk in expectation of the "too-many-to-fail" guarantee. Brown and Dinc (2009) is related to our paper, documenting evidence of the ex-post effect of "too-many-to-fail" that regulators are reluctant to close failed banks when other banks in the country are also weak.

Our empirical findings suggest large systemic risk-taking effect of public guarantees. Importantly, the findings unveil distortions as banks inefficiently underprice aggregate risk. Therefore, this paper has messages for public policy debate over banking regulation. First, banking regulation should focus on macroprudential regulation and operate at the collective level. Second, small and lowly correlated banks have been taking systemic risk aggressively and therefore need more regulator's attention.

The remainder of the paper is organized as follows. Section 4.2 sets out testable hypotheses. Section 4.3 presents the data, methodology and summary statistics. Section 4.4 examines evidence of bank systemic risk-taking from loan pricing. Section 4.5 analyzes the incentive for systemic risk-taking and highlights the importance of public guarantees. Section 4.6 tests the impacts of the "too-many-to-fail" guarantee on systemic risk-taking by examining the pricing patterns of banks of different interbank correlations and sizes. Section 4.7 concludes.

4.2. Hypotheses development

According to the portfolio theory, under the assumption of perfect diversification and no distortions, aggregate risk of the asset should be priced whereas diversifiable idiosyncratic risk should not. However, in the context of bank loans, idiosyncratic risk of the loans is likely to be priced but never more than aggregate risk for two reasons. First, most loan portfolios are imperfectly diversified or even limitedly diversified. Second, banks usually bear the losses from firm-specific defaults. However, if a bank expects to obtain bailout subsidies in a systemic crisis, then it may require lower compensation for aggregate risk relative to idiosyncratic risk as banks are less worried about losses in aggregate shocks in expectation of joint failure and collective bailout. Overall, distortions from the bailout policy lead banks to take systemic risk and underprice aggregate risk. This leads to the first hypothesis.

Hypothesis 1: *Banks require lower loan spreads for aggregate risk relative to idiosyncratic risk, indicating systemic risk-taking.*

Public guarantees can be a candidate for driving systemic risk-taking at banks. Since bailout guarantees are challenging to measure or proxy in a direct way, we use the presence (or absence) of public guarantees over banks (non-bank lenders) to test the impact of guarantees on risk-taking. In particular, banks are protected by explicit or implicit public guarantees that regulators and government will support them in a systemic crisis in the forms of capital injection or liquidity support. Hence banks could have incentives to take systemic risk. On the contrary, non-bank lenders which are not protected by any public guarantee should have no incentive to take systemic risk and therefore charge higher spreads for aggregate risk. Taken together, we propose the following hypothesis.

Hypothesis 2: *Non-bank lenders which are not protected by public guarantees do not take systemic risk and require higher loan spreads for aggregate risk relative to idiosyncratic risk.*

Acharya and Yorulmazer (2007) model the "too-many-to-fail" problem that a bank regulator finds it ex-post optimal to bail out failed banks when the number of failures is large, whereas the probability of the collective bailout is low when the number of bank failures is small, as failed banks can be acquired by surviving banks. The ex-post optimal bailout exists in the circumstance that the misallocation cost of liquidating bank assets to outside investors in case of systemic banking crisis exceeds the cost of injecting funds. Therefore, the bailout expectation creates incentives for banks to herd ex-ante in order to maximize the likelihood of failing together and therefore collective bailout. To test that systemic risk-taking is driven by the "too-many-to-fail" guarantee, we predict less correlated banks may be more aggressive in taking systemic risk as the marginal benefit of increased systemic risk could substantially raise the likelihood of joint failure and hence the collective bailout subsidy.

Hypothesis 3: *Less correlated banks take systemic risk more aggressively relative to more correlated banks.*

To corroborate the argument of "too-many-to-fail" effect, we predict smaller banks charge lower lending rates to aggregate risk, based on the prediction that smaller banks have stronger incentives to take systemic risk in Acharya and Yozulmazer (2007), different from the "too-big-to-fail" effect. This is because that the bailout subsidy increases in the systemic risk-taking for small banks when big banks also fail but it does not increase for big banks when small banks fail as big banks can acquire failed small banks (Acharya and Yorulmazer, 2007)

Hypothesis 4: *Smaller banks take systemic risk more aggressively relative to larger banks.*

4.3. Data, Methodology and Summary Statistics

4.3.1. Data

Syndicated loans provide an ideal laboratory to test systemic risk-taking at banks. First, syndicated loans are a vital source of corporate finance for large U.S. corporations (Sufi, 2007; Becker and Ivashina, 2014) and represent a substantial fraction of bank loan portfolios (Ivashina, 2009). Second, for each loan contract Dealscan provides rich information about the identities of borrowers and lenders which allow me to control for a variety of borrowers' and lenders' characteristics. Specifically, we can study how the characteristics of the banks (investors) of loans (assets) may affect the pricing. Last, non-bank lenders which are active in the syndicated loan market but are unprotected by bailout policies naturally constitute a control group for our test of the impact of public guarantees on systemic risk-taking.

Obtaining syndicated loan data from LPC Dealscan, we focus on U.S. firms borrowing from U.S. banks over the period between 1988 and 2011[41]. We exclude loans borrowed by companies in the financial sector from the sample (SIC codes 6000 to 6400, Finance and Insurance). Syndicated loans are usually structured in a number of facilities, also called tranches. We treat facilities in each deal as different loans because spreads, identity of lenders and other contractual features often vary within a syndicated loan deal[42]. Therefore, each observation in the regressions corresponds to a syndicated loan facility.

[41] Before 1987, the coverage of Deanscan is uneven. For an overview of the Dealscan database, see Strahan (1999).

[42] This is a common practice in the loan pricing literature. See similar analyses in Carey and Nini (2007), Focarelli, Pozzolo and Casolaro (2008), Santos (2011), Gaul and Uysal (2014).

By merging Dealscan with Compustat, we have detailed annual accounting information of the borrowers[43]. Compustat provides annual report data of publicly listed American companies, of which information problems are generally less severe than privately held firms.

In addition, we restrict our sample to loans taken out by companies of which stocks are actively traded because the proxies for idiosyncratic and aggregate risks are constructed based on stock market information. To calculate the equity volatility of borrowers, we collect daily stock return data from CRSP over the year leading up to the facility activation date for borrowers listed in NYSE, AMEX and NASDAQ[44]. We drop out borrowers with less than 100 trading days available in the event window[45]. Moreover, we collect Fama-French Factors from Wharton Research Data Services (WRDS).

Though our analysis of systemic risk-taking assumes a loan is made by a single lender, most of loans in our sample are syndicated by a number of leader arrangers and participants. This is less of a problem given our focus on the characteristics of lead arrangers. According to Dennis and Mullineaux (2000), Sufi (2007) and Santos and Winton (2008), leader arrangers are delegated to collect information and monitor the borrower on behalf of the syndicate[46]. In addition, leader arrangers set lending rates and non-pricing loan terms. By contrast, participants play a rather passive role in the syndicate. Therefore, it is a reasonable assumption that the lead arranger plays the role of the single bank lender in bilateral corporate lending of assessing the credit worthiness of the borrower and making decisions on risk-taking. Moreover, we restrict our sample to loans originated by a single lead arranger and exclude loans originated by multiple lead arrangers in order to clearly capture the effect of the lender's characteristics on loan pricing[47]. We manually match lead banks in Dealscan with commercial banks in

[43]We are indebted to Sudheer Chava and Michael Roberts for providing the link between Dealscan with Compustat, see Chava and Roberts (2008).

[44]We link LPC Deanscan with Compustat via GVKEY. Next, we use PERMNO to link Compustat with CRSP.

[45]Campbell and Taksler (2003) argue that a fairly long event window is required to measure the volatility that is publicly observed by corporate bond investors.

[46]Dealscan indicates the role of each lender. We follow the classification rule in Cai, Saunders and Steffen (2011). If the variable *LeadArrangerCredit* indicates "Yes", a lender is classified as a lead arranger. We correct for the role of lenders of loans that *LeadArrangerCredit* indicates "Yes" but "LenderRole" falls into participants as non-lead arrangers. In addition, if no lead arranger is identified, we treat a lender as a lead arranger if its "LenderRole" is classified as following items: Admin agent, Agent, Arranger, Bookrunner, Coordinating arranger, Lead arranger, Lead bank, Lead manager, Mandated arranger, Mandated Lead arranger.

[47]It makes little sense to aggregate lenders' characteristics (both leader arranger and participants) for

Call reports, depending on bank names, geographical locations and operating dates. We complement the unmatched sample of banking holding companies with Federal Reserve Y-9C reports. Additionally, we control for mergers and acquisition by matching the loan of the acquired lender to the accounting information of its acquirer.

To calculate the stock market based measure of interbank correlation, we collect banks' daily stock return data from CRSP one year preceding to the quarter of loan origination and the S&P 500 banking sector index from Datastream dating back to the last quarter of 1989. We link bank stock return with Call Reports and FY Y9C using the CRSP-FRB link from the Federal Reserve Bank of New York. In particular, we match commercial banks that are subsidiaries of the listed bank holding companies with the stock return data of their parent companies, similar to Lin and Paravisini (2012).

4.3.2. Loan pricing model

In the empirical analysis, we estimate the following loan pricing model:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 AggVol_{i,t-1} + \sum_j \gamma_j \mathbf{Firm}_{i,j,t-1} \\ &+ \sum_k \theta_k \mathbf{Loan}_{f,k,t} + \sum_n \psi_n \mathbf{Bank}_{b,n,t-1} + \sum_t \delta_t T_t + \epsilon_{i,f,b,t} \end{aligned} \tag{4.1}$$

where f, i, b and t denote facility, firm, bank and year, respectively. The dependent variable, *LoanSpread*, is the all-in-drawn spread in Dealscan which denotes an interest rate spread over LIBOR measured in basis points. It is summarized by Dealscan as a measure of overall costs of the loan, accounting for both one time and recurring fees. *IdioVol* and *AggVol* represent idiosyncratic and aggregate risks, respectively[48]. Moreover, we include firm specific variables ($\mathbf{Firm_i}$), loan specific variables ($\mathbf{Loan_f}$) and bank specific variables ($\mathbf{Bank_b}$). We also include year dummies T throughout all specifications. ϵ is the error term. We estimate the baseline loan pricing model by cross-sectional OLS regressions that pool together all valid observations. Robust standard errors are clustered at the lender level to correct for correlation across observations of a given lender, though the results hold when clustering at the levels of borrowers or the

loans with multiple lead arrangers. Nevertheless, our baseline results hold for loans granted by multiple lead arrangers.

[48] We do not include credit ratings of the borrower. The reason is that in principle credit rating should perfectly capture the default risk and therefore both idiosyncratic and aggregate risks would enter the regression insignificantly.

pairs of borrower-lender.

To compute the key independent variables, idiosyncratic and aggregate risks of the borrower, we rely on the borrower's equity volatilities which are forward-looking and are driven by market information. The idea is that we can think of the holder of risky debt as the owner of riskless bonds who have issued put options to the holder of firm equity (Merton, 1974). The strike price equals the face value of the debt and reflects limited liability of equity holders in the event of default. Increased equity volatility raises the value of put option, benefiting the equity holder at the expense of the debt holder. Hence a firm with more volatile equity is more likely to reach the bound condition for default. In addition, there is a burgeoning literature that applies equity volatility to explain credit spreads. In a seminal paper Campbell and Taksler (2003) find evidence that equity volatility, especially idiosyncratic equity volatility, has substantial explanatory power for corporate bond yields. Zhang, Zhou and Zhu (2009) and Ericsson, Jacob and Oviedo (2009) apply the same logic to credit default swap (CDS) pricing and find equity volatility is an important determinant of CDS spreads. Equity volatility has also been applied in empirical banking literature. Gaul and Uysal (2013) relate total equity volatility with loan spreads to explain the "global loan pricing puzzle" in Carey and Nini (2007). Santos and Winton (2013) use stock volatility as a proxy of the borrower's default risk. Acharya, Almeida and Campello (2013) also use equity beta to explain the cost of credit lines.

To decompose borrowers' equity volatility into idiosyncratic and aggregate components to proxy idiosyncratic and aggregate risks, respectively, we run a standard CAPM regression as follows:

$$r_{i,d} - r_d^f = \beta_{i,d}^{CAPM} \times (r_d^m - r_d^f) + \epsilon_{i,d} \tag{4.2}$$

where $r_{i,d}$, r_d^m and r_d^f represent individual stock daily return, market return calculated as the value-weight return on all NYSE, AMEX, and NASDAQ stocks in CRSP and risk free return proxied by the one-month Treasury bill rate, respectively. We define the idiosyncratic volatility as standard deviation of the residual, $IdioVol^{CAPM}{=}SD(\epsilon)$. In addition, we define the aggregate risk as the product of beta and market volatility, $AggVol^{CAPM}{=}\beta^{CAPM} \times MarketVol$, where $MarketVol$ is the standard deviation of market excess return ($SD(r^m - r^f)$).

Alternatively, we adopt Fama French three-factor model (Fama and French, 1993) using the following regression:

$$r_{i,d} - r_d^f = \alpha_{i,d} + \beta_{i,d}^{MKT} \times MKT_d + \beta_{i,d}^{SMB} \times SMB_d + \beta_{i,d}^{HML} \times HML_d + \varepsilon_{i,d} \tag{4.3}$$

Where the market factor MKT_d is the value-weight return on all NYSE, AMEX, and NASDAQ stocks from CRSP minus the one-month Treasury bill rate, the size factor SMB_d is the average return on the three small portfolios minus the average return on the three big portfolios, the value factor HML_d is the average return on the two value portfolios minus the average return on the two growth portfolios, respectively. We stick to the standard deviation of the residual $IdioVol^{FF} = SD(\varepsilon)$ as the idiosyncratic volatility. On the other hand, following Bali, Brown and Caglayan (2012) we define the aggregate risk in the multifactor model as the total volatility that is attributable to Fama French factors and the factors' cross-covariances, $AggVol^{FF} = \sqrt{(TotalVol)^2 - (IdioVol^{FF})^2}$. In the end, we annualize all equity volatilities by a multiplier of $\sqrt{252}$ as daily stock returns are used.

We include a number of firm level controls that may affect the lending interest rates. Log(Sales) is the logarithm of the firm's sales at close in millions of dollars. Larger firms are more informationally transparent, therefore we expect larger borrowers have lower spreads. Next, LEVERAGE is a ratio of total debts to total assets. Highly leveraged firms are more likely to default and hence are expected to be charged a higher lending rate. Besides, we control for PROFMARGIN which is defined as a ratio of profit margin to firm sales, and ROA which is return on assets, to measure the performance and profitability of the borrower. As a highly profitable firm is safer and less likely to fall into financial distress, it should be charged a lower spread. As for the firm specific controls that affect loss given default (LGD), we include new working capital and tangibles assets. NWC measures a ratio of net working capital to total assets. Firms with more net working capital are expected to lose less value in the event of default. In addition, TANGIBLE measures a fraction of tangible assets to total assets. Borrowers with a higher fraction of tangible assets are more informationally transparent (Morgan, 2001) and have higher values in the event of default as the value of intangible assets are much volatile. Therefore we expect a lower spread on the loans taken out by borrowers with a higher fraction of tangible assets. We control for Market-to-Book ratio, MKTBOOK, an imperfect proxy of Tobin's q, which is a ratio of the market value of a firm to its accounting value. We expect a firm with a higher Market-to-Book ratio to have lower spreads. Finally, we include industry dummies that classify borrowers into ten sectors based on 4-digit SIC codes, considering that loss given default (LGD) is strongly correlated with industry characteristics (Hertzel and Officer, 2012; James and Kizilaslan, 2014). Our results hold if we alternatively use dummy variables for two-digit SIC industry groups.

Even though nonpricing loan specific variables are jointly determined with loan spreads and therefore are endogenous, we include these contractual terms. We include Log(FacilitySize), measured by the log of the facility amount in millions of dollars. Large loans are likely to be associated with greater credit risk in the underlying project and lower liquidity, but could also be borrowed by larger firms which have more cushions against adverse shocks. Therefore, the impact of loan size on loan pricing is not unambiguous. Additionally, we include MATURITY which is the maturity of the facility in years. The effect of maturity on loan spreads is also ambiguous. Next, we use the number of lenders in a facility (#Lenders) and the number of facilities within a deal (#Facilities) to proxy the syndicated structure. To measure the liquidity exposure of each facility, we classify a loan as a line of credit (REVOLVER) or a term loan (TERMLOAN)[49]. Moreover, we include dummy variables that indicate whether a loan is senior (SENIOR) in the borrowers' liability structure and whether the loan is secured by collateral (SECURED). Seniority and collateral may reduce the lenders' loss in the event of borrower default and therefore reduce lending rates, however, the contractual arrangement may be required ex-ante to protect lenders towards specifically risky borrowers. Therefore, the relation between seniority, collateral and loan pricing is an empirical question. Last, we control for loan purpose dummies into five categories: Corporate Purpose, Debt Repayment, Takeover, Working Capital and Other.

As the loan contract is negotiated between the borrowers and lenders, lenders' characteristics may also affect contract terms and have been incorporated into the analysis of loan pricing recently. Analyzing the effect of banks' financial health on loan spreads,

[49]In particular, a loan is classified as a revolver is the loan type is expressed in Dealscan as "364-Day Facility", "Revolver/Line < 1 Yr.", "Revolver/Line >= 1 Yr.", "Revolver/Term Loan", "Demand Loan", "Limited Line". Alternatively, a loan is defined as a term loan if the loan type is recorded as "Term Loan", "Term Loan A", "Term Loan B", "Term Loan C", "Term Loan F", "Delay Draw Term Loan".

Hubbard, Kuttner and Palia (2002) find less capitalized bank charge higher spreads than well capitalized banks. Examining how bank capital, borrower cash flow and their interaction affect loan pricing, Santos and Winton (2013) show that less capitalized banks charge relatively more for borrowers with low cash flow but offer discounts for borrowers with high cash flow. Santos (2010) emphasizes the impacts of bank losses on loan contracts. He shows evidence of credit crunch in the subprime crisis that even though firms paid higher loan spreads and took out smaller loans during the subprime crisis, the increase in loan spreads was higher for firms that borrowed from banks that incurred large losses. In this study we consider following bank specific variables of lead arrangers. First, we include SizeBK as the logarithm of bank total assets in millions of dollars. Large banks usually have diversified portfolios and good risk management, therefore we expect large banks charge low lending rates. Next, we control for CapitalBK, denoted as a ratio of bank capital to total assets. Well capitalized banks have more capital buffer and therefore are expected to charge a lower spread. In addition, we use NPLBK, a ratio of nonperforming loans to total assets, as a measure of bank credit risk. Risky banks may charge additional compensation for undertaking extra risk. Hence, we expect banks with a higher proportion of nonperforming loans to charge a higher spread. We also use ZscoreBK as a direct measure of bank insolvancy risk. We calculate Z score following Laeven and Levine (2009) but use an eight-quarter rolling window. Moreover, we include a bank profitability measure ROABK. More profitable banks are expected to charge a lower rate. To control for the impact of bank liquidity on loan rates, we include LiquidityBK to measure the liquidity of bank assets, which is a ratio of sum of liquid securities and cash to total assets. Besides, we use the growth rate of loans (LoanGrowthBK) to measure investment opportunities of the lender. In the end we include CostOfFundBK which is total interest expenses over total liabilities to measure funding costs.

In particular, we use the accounting information of the borrower and lenders from the fiscal year ending in the calendar year $t-1$ for loans made in calendar year t. To eliminate the bias from outliers, we winsorize loan spreads, firm and bank specific variables and borrowers' equity volatilities at 1 and 99 percentile levels[50]. We include year dummies to capture time trends throughout the analysis as Santos (2011) has shown the business

[50]See Appendix Table A.1 for detailed information of variables.

cycle effect on loan contracts.

4.3.3. Summary Statistics

The final sample consists of 11,323 facilities taken out of 4,192 publicly listed U.S. nonfinancial firms from 464 U.S. lead banks over the period 1988 to 2011. Table 4.1 presents summary statistics of the sample. The average all-in-drawn spread is 207 basis points over LIBOR. The average CAPM idiosyncratic volatility is 0.554, very close to the mean of total volatility. Since market is usually relatively stable, the average aggregate volatility which is the product of Beta and market volatility is rather small (0.116), much smaller than the average beta (0.758). It is worth noting that aggregate volatility could be negative as the beta of some borrowers is negative. Overall, the idiosyncratic and aggregate volatilities estimated from CAPM and Fama French three-factor models are quite similar.

Looking at firm level controls, we find the average log of firm total assets is 5.611. The mean of borrowers' leverage is 28.035%. The profit margin is highly skewed, with a mean of -0.871% and a median of 3.211%. The mean of net working capital to total assets and tangible assets to total assets are 21.107% and 69.036%, respectively. The average Market-to-Book ratio is 1.782.

We turn to the loan controls in the sample. The average logarithm of facility amount is 3.805. It is worth noting that the log of facility size can be negative when the loan is pretty small. Syndicated loans in the sample have an average maturity of 3.589 years. In addition, on average each syndicate has 6 lenders and is structured into 1.763 facilities. Looking at the loan types, 73% of loans are lines of credit while 24% are term loans. Almost all loans are senior in the borrower's liability structure. In the end, 75% of loans are secured by collateral.

We check the sample characteristics of banks. Except bank size and z score which are log adjusted, the rest bank specific variables are expressed in ratios. Banks are much larger as the average log of bank total assets is 11.269. The average equity to asset ratio is 7.524%. Both the average share of nonperforming loans to gross loans and the average ROA are 0.952%. The mean of bank Z score is 3.179. Liquid assets account for 18.716% of total assets. The median of loan growth rate is 9.191% although the average is rather high at 20.476%. The average bank has the cost of funds at 3.390%. As not all banks are listed and traded in stock exchanges, we have the information of interbank correlation for approximately 9321 facilities, of which the average interbank correlation is 0.735.

4.4. Evidence of bank systemic risk-taking from the pricing of idiosyncratic and aggregate risks

In this section, we apply the baseline loan pricing model to examine bank systemic risk-taking. Table 4.2 reports the results using idiosyncratic and aggregate risks estimated from the CAPM regression. In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. In column 1, we regress loan spreads on equity volatilities and year dummies only. The coefficient of the idiosyncratic volatility is positive and significant, indicating banks charge risk premium for bearing idiosyncratic default risk of the borrower. On the contrary, the coefficient of aggregate risk is negative and significant, suggesting that banks do not charge risk premium but rather offer lending rate discounts to aggregate exposure, consistent with hypothesis 1 that banks take systemic risk. In column 2, the main results are insensitive to the inclusion of firm level balance sheet variables and industry dummies[51]. In addition, the firm characteristics have expected signs and are mostly significant. In particular, we find that larger firms, firms with higher profit margins, and less leveraged firms pay lower loan spreads. Proxies for net working capital and tangible assets have expected signs and are statistically significant. The market to book ratio is marginally significant and negatively associated with loan spreads. In column 3 we further control for loan specific variables, despite that loan spreads and other contract terms are simultaneously determined. The hypothesis 1 continues to be supported. Moreover, we find that larger loans and loans with longer maturity are charged at a higher rate. The two proxies of syndicate structure have opposite effects. In particular, loans of more lenders in the syndicate are associated with lower spreads, whereas loans with more facilities are more expensive. Moreover, lines of credit are generally cheaper. A loan is much cheaper if it is senior when it

[51]The number of observations in the regressions drops due missing values in industry classification.

ensures the priority of the lender to claim to residual value in the event of borrower bankruptcy. Furthermore, a secured loan is charged a higher spread than a similar one without collateral probably because only risky borrowers are required for collateral and are ex-ante charged a risk premium. In column 4, we add bank level controls, provided that the lender' characteristics may have impacts on loan pricing. As a result, our main results of systemic risk-taking continue to hold. Specifically, banks do charge a sizable spread on idiosyncratic risk. A firm of which idiosyncratic risk is one standard deviation (0.303) greater than the sample mean pays 28 ($= 91.778 \times 0.303$) basis points extra. By contrast, a one standard deviation (0.101) increase in the aggregate risk lowers the loan interest rate by 4 ($= -42.850 \times 0.101$) basis points. Though the spread undercut on aggregate risk is not economically significant, it indicates that banks do not charge risk premium to cover the potential losses to aggregate shocks. Furthermore, we find that larger banks, well-capitalized banks, banks with high costs of funding and banks with high loan growth rates charge lower spreads while risky banks charge relatively higher spreads.

We do the same exercise using equity volatilities estimated from the Fama French three-factor model in Table 4.3. Overall, all estimates preserve the sign, significance and magnitude with the baseline results using CAPM equity volatility. Again, the results hold when standard errors are clustered at the bank level (or firm-bank pair level) to correct for correlation across a given bank (bank-firm pair). For brevity, in the following output tables we do not report the estimated coefficients of firm, loan and bank specific control variables.

Table 4.4 shows that our results are insensitive to various alternative estimates of idiosyncratic and aggregate risks. Even though equity beta is not comparable to volatility, we use CAPM beta ($Beta^{CAPM}$) and market beta in the Fama French three-factor model ($Beta^{MKT}$) as alternative measures of aggregate exposure. We find similar evidence that banks charge lower spreads for aggregate risk in columns 1 and 2. In addition, controlling for both total volatility ($TotalVol$) and a share of aggregate volatility in total volatility ($AggVol^{CAPM}/TotalVol$, $AggVol^{FF}/TotalVol$) as key explanatory variables in columns 3 and 4, we find that the coefficient of total volatility is positively and significantly associated with lending rates, whilst the coefficient of aggregate volatility enters negatively and significantly.

The use of equity volatility in our analysis relies on a crucial assumption that equity volatility captures the credit risk associated with the unobserved firm asset volatility. However, contingent claims model suggests equity volatility is a complex function of both asset volatility and leverage. A caveat may arise if, although leverage is a source of firm-specific credit risk, it can amplify or weaken the asset volatility effect and therefore contaminate the estimated effect of equity volatility (Campbell and Taksler, 2003; Gaul and Uysal, 2013). For instance, Campbell and Taksler (2003) argue that debt holders of a company with a very small amount of debt are not worried about insolvency even if the equity is volatile. To better capture the credit risk, we deleverage equity volatility as in James and Kizilaslan (2014) by a multiplier of equity/(debt+equity), in which equity is the borrower's market capitalization and debt is the sum of short term debt and half of long term debt. We report the results in the last two columns where the unlevered equity volatilities yield similar results to our baseline regressions. In particular, the coefficient of unlevered aggregate volatility remains significant and negative, continuing to support our hypothesis.

The baseline specification may be prone to omitted variable bias if unobserved firm characteristics drive both firm's equity volatility and loan spreads. We restructure the data set into panel data in which we have the cross section unit, i=firm, and the time series unit, f=facility. We estimate a firm fixed effects model, allowing for arbitrary correlation between the unobserved borrower effect and the observed explanatory variables. The identification comes from variations in equity volatility and loan spreads within the same firm. In particular, we compare loan spreads of the same firm across different loans when equity volatilities differ before the loan origination. The results in the first two columns of Table 4.5 further confirm the findings that idiosyncratic volatility is positively priced and aggregate volatility is negatively priced. The weak significance of aggregate volatility is the result of a short dimension along facilities within the borrower as each firm borrows on average 2.7 facilities in the sample[52].

Likewise, another caveat would arise if unobserved bank characteristics might be correlated with lending interest rates. For instance, showing that a bank's stock performance during the 1998 crisis predicts the stock performance and probability of failure in

[52] The information loss arising from the short times series dimension for each cross section unit may weaken the identification in panel data estimations.

the recent financial crisis, Fahlenbrach, Prilmeier and Stulz (2012) suggest that banks' business model or risk culture may be persistent over time. The unobserved business model or risk culture may have a non-negligible impact when the bank decides the loan interest rates. To rule out the effect of unobserved bank characteristics on pricing patterns, we reorganize the sample into panel data in which b=bank is the cross-section unit and f=facility is the time series unit. We estimate a bank fixed effects model that eliminates the unobserved bank specific effects which are heterogenous across lenders but are constant over facilities of the same lender. Our results largely hold in Columns 3 and 4. The highly statistical significance comes from the fact that each bank lends on average 30 facilities in the sample.

Taken together, we find that loan spreads are positively associated with idiosyncratic risk but negatively associated with aggregate risk of the borrower. The lending rate discount to aggregate risk can be interpreted as evidence of systemic risk-taking in syndicated loans. In the next section, we investigate the incentives for banks taking systemic risk.

4.5. Systemic risk-taking and public guarantees: Do non-bank lenders take systemic risk as well?

Although non-bank institutional investors have been actively participating in the syndicated loan market especially in the leveraged loan segment since 2000, loans originated by non-bank lenders to publicly traded U.S. nonfinancial companies remained substantially fewer than similar bank loans[53]. We collect 1789 loans originated by non-bank institutional investors, for instance, finance companies, corporations, mutual funds, trust companies, insurance companies and so forth, which are not protected by public bailout guarantees[54]. For comparison, we collect bank loans originated by commercial banks, bank holding companies, thrifts, savings and loan associations (S&Ls). Because the status of investment banks and mortgage banks are ambiguous in bailouts in a sense that

[53]For descriptions of the role of non-bank lenders in the syndicated loan market, see Ivashina and Sun (2011).

[54]None of the four insurance companies in our sample, Equitable Life Assurance Society of the US, Prudential Insurance Co of America, Northwestern National Life, New York Life Insurance Co, are bailout recipients.

they are not strictly protected by public guarantee ex-ante but often obtain government support ex-post in a systemic crisis, we exclude the two types of lenders from the sample. Table A.2 displays the composition of our sample. One can see the majority of the non-bank loans come from finance companies.

We report the regression output for the loan pricing patterns by non-bank lenders and bank lenders in Table 4.6. As the accounting information for non-bank lenders is not as readily accessible as banks, we only control for borrower and loan specific variables as well as year dummies[55]. We find that both aggregate risk and idiosyncratic risks are priced similarly by non-bank lenders in columns 1 and 3. In particular, the estimated coefficient for aggregate risk is positive, significant, and slightly greater that the coefficient of idiosyncratic risk, in line with the prediction of the portfolio theory. In other words, non-bank lenders charge a risk markup for aggregate risk in the absence of public guarantees. In columns 2 and 4 the main results that banks charge lower lending rates to aggregate risk still hold. Overall, given that banks provide lending interest rate discounts to aggregate risk whereas non-bank lenders charge a significantly positive risk premium for aggregate risk, we conclude that the key distinction between the two cohorts of lenders, namely, the coverage of public guarantees, determines pricing patterns and systemic risk-taking at banks.

One concern may arise that our finding of the different pricing patterns of bank and non-bank loans could be the result of spurious correlation. For instance, banks serve observably less risky borrowers whereas non-bank lenders especially finance companies cater to observably more risky firms (Carey, Post and Sharpe, 1998). This is indeed reflected in our sample. The first three columns of Table 4.8 summarize the firm-specific covariates of loans originated by banks and non-bank lenders, respectively. The t-tests of the sample means suggest that non-bank lenders serve borrowers which have higher idiosyncratic stock volatility, smaller size, higher leverage and lower profitability.

Although this lending specialization may be one omitted driver of pricing discrepancy, this caveat is unlikely to bias our findings for two reasons. First, estimating the loan pricing models for the subsamples of bank loans and non-bank loans separately could control for this possibility. Second, even if lending specialization affects the selection

[55] The number of bank loan observations is greater here than in the baseline regression because we avoid attrition in the procedure of matching loans with bank accounting variables.

of the riskiness of borrower and therefore loan rates, it can only explain why non-bank lenders charge positive loan spreads on both idiosyncratic and aggregate risks to risky borrowers. Albeit it cannot explain the lending rate discount by banks without the introduction of banking regulation, particularly bailout subsidies.

Nevertheless, matching techniques could be introduced to address this concern of selection on observables, namely, lenders may select their clients based on borrowers' characteristics (Tucker, 2010). In particular, we can address the issue of imperfect comparability of bank and non-bank borrowers by employing propensity score matching. We take the pool of loans by non-bank borrowers as the treatment group and search for a control group of loans by bank borrowers which are similar to non-bank borrowers in all dimensions (based on observable firm controls).

When applying the propensity score matching algorithm, we first estimate a Probit model to predict the likelihood of a firm to borrow from a non-bank lender. Therefore, the dependent variable is a dummy which takes 1 if the loan is originated by a non-bank lender, and 0 if by a bank. The Probit regression includes idiosyncratic and aggregate risks, firm-specific controls, industry dummies, and year dummies[56]. Robust standard errors are clustered at the lender level. The results are presented in column 1 of Table 4.7, which indicates idiosyncratic risk, leverage, profitability and market-to-book value have significant impacts on the probability of borrowing from a non-bank lender. The p-value of χ^2 test of the model fitness of 0.000 suggests that before matching, firm-specific variables can explain a significant amount of variations in the choice of lenders. Next, we use the propensity score to perform a nearest-neighbor propensity score matching. To avoid bad matches, we impose a tolerance level of 0.05% on the maximum propensity score distance allowed. In the end, each loan originated by a non-bank lender is matched to a loan in the control group with the closest propensity score in terms of the borrowers' characteristics. We end up with 1549 pairs of matched loans[57].

Since our identification depends crucially on the conditional independence assumption, which assumes after matching the choice of lender type is randomly assigned, we

[56] We are unable to match, however, on the lenders' characteristics which are partially unobservable for the group of non-bank lenders.

[57] The number of matched loan is smaller than in Table 4.6 as we impose common support restriction which drops treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls, and trim (5%) which drops 5% of the treatment observations at which the propensity score density of the control observations is the lowest. The two restrictions substantially improve the quality of matching.

conduct two diagnostic tests to verify this assumption holds. First, we re-estimate the Probit model restricted to the matched sample in column 2 of Table 4.7. None of the explanatory variable is significant. Moreover, the p-value of the χ^2 test is 0.998, suggesting that we cannot reject the null hypothesis that all of the estimated coefficients are zero. This supports the validity of conditional independence assumption in the matched sample. Second, we conduct the univariate comparisons of firms' characteristics after matching in the last three columns of Table 4.8. None of the observable differences of the borrowers is statistically significant. Overall, the diagnostic tests assure that propensity score matching yields a matched sample which is more homogenous and less prone to selection bias.

We re-estimate our non-bank versus bank tests in Table 4.9. Despite a drop in sample size, we obtain similar results as in Table 4.6.

4.6. Too-many-to-fail

We directly test the "too-many-to-fail" argument by assessing the impact of interbank correlations on loan pricing. The idea is that less correlated banks have stronger incentives to increase interbank correlation and therefore take systemic risk in order to maximize the likelihood of failing together with systemically important banks. Therefore "too-many-to-fail" argument predicts that less correlated banks charge lower spreads to aggregate risk compared to more correlated banks[58]. To measure interbank correlations, we first calculate the correlation of the bank's daily excess return with the S&P 500 banking sector index using the data one year prior to the quarter of loan origination. Since the data of S&P 500 banking sector index start from the Q4 1989, the sample consisting of 9 321 loans taken out by 3562 firms from 259 publicly listed banks, is slightly shorter and smaller than the one used in the baseline analysis. We construct a dummy variable $LowCorrBK$ that equals one if a bank's interbank correlation is smaller than the median value and zero otherwise. Interacting the bank correlation with

[58]This analysis rests on an assumption that ex-ante banks make decisions on lending and pricing, given the existing loan portfolios and therefore interbank correlations. However, it is possible that a single loan can affect interbank correlations ex-post, depending on the aggregate exposure and relative size of the loan amount to bank assets.

borrowers' equity volatilities, we estimate the following model:

$$\begin{aligned}
LoanSpread_{i,f,b,t} = & c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 AggVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times LowCorrBK_{b,t-1} \\
& + \alpha_4 AggVol_{i,t-1} \times LowCorrBK_{b,t-1} + \alpha_5 LowCorrBK_{b,t-1} \\
& + \sum_j \gamma_j \mathbf{Firm}_{i,t-1} + \sum_k \theta_k \mathbf{Loan}_{f,t} + \sum_n \psi_n \mathbf{Bank}_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t}
\end{aligned} \tag{4.4}$$

The results based on CAPM equity volatilities are presented in column 1 in Table 4.10. We find the idiosyncratic volatility is positively associated with loan spreads, suggesting that banks charge a risk premium for bearing the firm-specific default risk. On the contrary, the coefficient of aggregate risk is negative but insignificant. The interaction term between idiosyncratic volatility and low correlation dummy is positive and significant. The interaction between aggregate volatility and low correlation dummy is negative and significant, suggesting that less correlated banks charge lower lending rates on aggregate risk relative to more correlated banks. Taken together, we find less correlated banks underprice aggregate risk more relative to more correlated banks.

To relax the restrictions of identical coefficients of the firm, loan and bank specific covariates for the two subgroups of lowly and highly correlated banks in the baseline regression, we divide the sample into two corresponding subsamples. The results of sample split are given in the columns 3 and 5. We find that aggregate risk is negatively and significantly priced by less correlated banks whereas insignificantly priced by more correlated banks. This indicates less correlated banks have stronger incentives to take aggregate risk of borrowers and therefore increase systemic risk. Doing the same exercise using Fama French equity volatilities, we have similar results in columns 2, 4 and 6. Overall, we find evidence that less correlated banks have stronger incentives to underprice aggregate risk and therefore take systemic risk, consistent with the "too-many-to-fail" story.

Since the test of "too-many-to-fail" based on banks' stock information may be biased by sample selection as the sample is restricted to publicly listed banks and excludes numerous unlisted small banks[59]. To correct for the sample bias, we also test the

[59] These are relatively small lenders in the syndicated loan market, but not necessarily small banks in the absolute terms. The average size of the small banks is 15.9 billion USD.

hypothesis that smaller banks are more aggressive in systemic risk-taking driven by "too-many-to-fail", as suggested by Acharya and Yozulmazer (2007). To test the impact of bank size on risk pricing, we construct a dummy variable *SmallBK* that equals one if the bank size is below the median value, and zero otherwise. The small bank dummy is then interacted with borrowers' equity volatilities. Overall, we run the following regression:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 AggVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times SmallBK_{b,t-1} \\ & + \alpha_4 AggVol_{i,t-1} \times SmallBK_{b,t-1} + \alpha_5 SmallBK_{b,t-1} \\ & + \sum_j \gamma_j \mathbf{Firm}_{i,t-1} + \sum_k \theta_k \mathbf{Loan}_{f,t} + \sum_n \psi_n \mathbf{Bank}_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t} \end{aligned} \tag{4.5}$$

We present the results in Table 4.11. In column 1, we find banks generally charge a higher spread for idiosyncratic risk. The coefficient for aggregate risk and the interaction between idiosyncratic risk and *SmallBK* are negative and insignificant. However, the interaction term between aggregate risk and *SmallBK* is negative and significant, suggesting that small banks underprice aggregate risk relative to big banks. In the end, the coefficient of *SmallBK* is positive but insignificant. Overall we find small banks underprice aggregate risk to idiosyncratic risk more relative to big banks do, indicating that small banks are more aggressive in taking systemic risk. For sensitivity analysis, we split the full sample into loans originated by small and big banks and report the results in columns 3 and 5. Our results continue to hold. The exercises based on Fama French equity volatilities in columns 1, 4 and 6 yield similar results. Taken together, we find small banks tend to underprice aggregate risk, which is different from the prediction of "too-big-to-fail" theory which asserts that large banks are likely to take risk to exploit the safety net.

4.7. Conclusion

This paper documents evidence of bank systemic risk-taking from loan pricing. We find loan spreads are positively associated with borrowers' idiosyncratic risk but negatively associated with aggregate risk. The lending rate discount for aggregate exposures reveals banks' preference for increased correlation and systemic risk. Relating this collective moral hazard to the "too-many-to-fail" guarantee in banking regulation, we show that no evidence of such systemic risk-taking could be found in the loans originated by non-bank lenders in absence of bailout expectation. In line with the "too-many-to-fail" theory in Acharya and Yorulmazer (2007), we find less correlated banks and smaller banks are more aggressive in systemic risk-taking as they underprice aggregate risk of the borrower more relative to more correlated banks and larger banks, respectively. The findings also suggest that the results are not driven by the "too-big-to-fail" guarantee.

Our findings have direct policy implications for macroprudential regulations. First, the fact that banks take advantage of the financial safety net and pass through regulatory subsidies to borrowers in the form of inappropriate pricing of risk may threat the stability of the entire banking sector. The prudential regulation should be designed to force banks to internalize the social costs incurred in systemic crises so that the incentive for systemic risk-taking is ameliorated. In particular, banking regulation should operate at the collective level to pay more attention to systemic risk on top of individual risk to cope with the collective moral hazard of systemic risk-taking (Acharya, 2009; Farhi and Tirole, 2009). For instance, systemic risk capital buffer requirement could be introduced as a policy instrument for macroprudential regulation. One recent example is that the Dutch central bank, De Nederlandsche Bank (DNB), intends to impose an additional capital buffer requirement on the four systemic banks in the Netherlands. In particular, this systemic buffer will be 3% of risk-weighted assets for ING Bank, Rabobank and ABN AMRO Bank, and 1% for SNS Bank. Second, much attention has been paid to systemically important financial institutions (SIFIs) which contribute substantially to systemic risk. However, in this paper we show that small and lowly correlated banks have been aggressive in taking systemic risk and need attention for regulation as well. Therefore, extra capital buffer requirement based on asset correlation, which is applied to every bank as capital requirement based on individual credit risk, could be a desirable policy instrument for macroprudential regulation.

Table 4.1: Summary Statistics

	No.	Mean	Std. Dev	Min	Median	Max
LoanSpread	11323	206.819	119.832	20.000	200.000	578.080
Borrower Equity Volatilities						
TotalVol	11323	0.575	0.303	0.171	0.500	1.709
MarketVol	11323	0.155	0.064	0.078	0.127	0.398
$IdioVol^{CAPM}$	11323	0.554	0.303	0.155	0.482	1.697
$AggVol^{CAPM}$	11323	0.116	0.101	-0.054	0.096	0.529
$IdioVol^{FF}$	11323	0.545	0.301	0.152	0.470	1.688
$AggVol^{FF}$	11321	0.154	0.103	0.021	0.129	0.585
$Beta^{CAPM}$	11323	0.758	0.564	-0.427	0.692	2.471
$Beta^{MKT}$	11323	0.965	0.624	-0.627	0.945	2.800
$Beta^{SMB}$	11323	0.833	0.787	-1.030	0.768	3.190
$Beta^{HML}$	11323	0.294	0.964	-2.593	0.301	3.131
Firm controls						
Log(Sales)	11323	5.611	1.729	1.635	5.563	9.847
LEVERAGE	11323	28.035	20.687	0.000	26.606	92.863
PROFMARGIN	11323	-0.871	22.044	-149.972	3.211	28.587
ROA	11323	12.193	11.015	-35.071	12.819	39.983
NWC	11323	21.107	20.804	-28.733	19.291	74.215
TANGIBLES	11323	69.036	36.672	5.675	66.819	177.554
MKTBOOK	11323	1.782	1.072	0.668	1.453	6.815
Loan controls						
Log(FacilitySize)	11323	3.805	1.767	-2.996	3.912	10.086
Maturity	11323	3.589	2.098	0.083	3.083	23.000
#Lenders	11323	6.050	7.716	1	3	113
#Facilities	11323	1.763	0.987	1	1	8
REVOLVER	11323	0.730	0.444	0	1	1
TERMLOAN	11323	0.244	0.429	0	0	1
SENIOR	11323	0.999	0.038	0	1	1
SECURED	11323	0.751	0.432	0	1	1
Corporate Purpose	11323	0.228	0.420	0	0	1
Debt Repayment	11323	0.247	0.431	0	0	1
Takeover	11323	0.166	0.372	0	0	1
Working Capital	11323	0.127	0.333	0	0	1
Other Purpose	11323	0.233	0.422	0	0	1
Bank controls						
SizeBK	11323	11.269	1.878	6.220	11.315	14.358
CapitalBK	11323	7.524	1.940	3.594	7.247	14.886
ROABK	11323	0.952	0.580	-1.693	1.037	2.215
ZscoreBK	11323	3.179	0.464	0.888	3.249	4.033
NPLBK	11323	0.936	1.022	0.000	0.556	4.912
LiquidityBK	11323	18.716	8.573	3.925	18.150	46.141
LoanGrowthBK	11323	20.476	38.342	-35.727	9.191	199.013
CostOfFundBK	11323	3.390	1.653	0.522	3.313	10.520
InterbankCorr	9321	0.735	0.161	-0.267	0.778	0.980

Table 4.2: Baseline regression CAPM

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. We use equity volatilities estimated from CAPM regressions. In column 1, we include equity volatilities only as explanatory variables. In column 2, we add firm specific variables as controls. In column 3, we further add loan specific variables as controls. In column 4, we include bank specific variables as well. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$IdioVol^{CAPM}$	216.469***	129.264***	92.632***	91.788***
	(9.008)	(7.195)	(6.113)	(6.108)
$AggVol^{CAPM}$	-173.098***	-54.640***	-40.841***	-42.850***
	(20.374)	(15.442)	(14.337)	(14.273)
Log(Sales)		-20.732***	-6.497***	-6.010***
		(1.234)	(0.897)	(0.924)
LEVERAGE		0.984***	0.667***	0.676***
		(0.081)	(0.066)	(0.061)
PROFMARGIN		0.100	0.107	0.107
		(0.101)	(0.080)	(0.079)
ROA		-1.589***	-1.587***	-1.517***
		(0.235)	(0.167)	(0.142)
NWC		-0.249***	-0.251***	-0.257***
		(0.074)	(0.065)	(0.064)
TANGIBLES		-0.130***	-0.029	-0.036
		(0.041)	(0.032)	(0.032)
MKTBOOK		-0.060***	-0.010	-0.014
		(0.019)	(0.012)	(0.010)
Log(FacilitySize)			-9.513***	-8.491***
			(1.484)	(1.286)
Maturity			-4.167***	-4.042***
			(0.895)	(0.875)
#Lenders			-0.494***	-0.573***
			(0.167)	(0.164)
#Facilities			12.747***	13.083***
			(1.844)	(1.803)
REVOLVER			-37.931***	-37.681***
			(9.040)	(8.864)
TERMLOAN			-8.106	-7.624
			(10.546)	(10.367)
SENIOR			-190.679***	-193.901***
			(33.629)	(33.628)
SECURED			72.487***	72.047***
			(2.692)	(2.557)
SizeBK				-4.370***
				(1.261)
CapitalBK				-2.415***
				(0.916)
ROABK				1.173
				(3.162)
ZscoreBK				-2.274

				(3.695)
NPLBK				3.650*
				(2.136)
LiquidityBK				-0.265
				(0.229)
LoanGrowthBK				-0.073**
				(0.029)
CoftOfFundBK				-3.102
				(2.734)
Constant	171.445***	312.103***	421.445***	490.482***
	(12.735)	(13.282)	(36.335)	(40.460)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes
Loan Purpose Dummies	No	No	Yes	Yes
Observations	11,323	11,323	11,323	11,323
Adjusted R-squared	0.340	0.439	0.557	0.561

Table 4.3: Baseline regression Fama French

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. We use equity volatilities estimated from Fama French regressions. In column 1, we include equity volatilities only as explanatory variables. In column 2, we add firm specific variables as controls. In column 3, we further add loan specific variables as controls. In column 4, we include bank specific variables as well. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$IdioVol^{FF}$	230.749***	134.597***	96.190***	95.415***
	(8.474)	(6.953)	(5.917)	(5.878)
$AggVol^{FF}$	-172.813***	-54.616***	-38.262**	-39.739**
	(20.038)	(16.470)	(16.248)	(16.329)
Log(Sales)		-20.628***	-6.495***	-6.018***
		(1.248)	(0.905)	(0.933)
LEVERAGE		0.981***	0.665***	0.674***
		(0.082)	(0.067)	(0.062)
PROFMARGIN		0.102	0.109	0.110
		(0.100)	(0.079)	(0.079)
ROA		-1.590***	-1.586***	-1.517***
		(0.232)	(0.166)	(0.141)
NWC		-0.240***	-0.246***	-0.252***
		(0.074)	(0.065)	(0.064)
TANGIBLES		-0.130***	-0.028	-0.036
		(0.041)	(0.033)	(0.032)
MKTBOOK		-0.059***	-0.010	-0.014
		(0.019)	(0.012)	(0.010)
Log(FacilitySize)			-9.440***	-8.417***
			(1.481)	(1.291)
Maturity			-4.185***	-4.061***
			(0.896)	(0.876)
#Lenders			-0.502***	-0.580***
			(0.167)	(0.164)
#Facilities			12.692***	13.028***
			(1.852)	(1.813)
REVOLVER			-37.656***	-37.416***
			(9.054)	(8.883)
TERMLOAN			-7.871	-7.395
			(10.547)	(10.374)
SENIOR			-190.935***	-194.210***
			(33.531)	(33.538)
SECURED			72.575***	72.134***
			(2.688)	(2.552)
SizeBK				-4.372***
				(1.259)
CapitalBK				-2.383***
				(0.911)
ROABK				1.239
				(3.144)
ZscoreBK				-2.220

				(3.692)
NPLBK				3.627*
				(2.137)
LiquidityBK				-0.269
				(0.228)
LoanGrowthBK				-0.074**
				(0.029)
CostOfFundBK				-3.072
				(2.745)
Constant	178.400***	314.396***	423.049***	491.838***
	(13.451)	(13.320)	(36.406)	(40.430)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes
Loan Purpose Dummies	No	No	Yes	Yes
Observations	11,321	11,321	11,321	11,321
Adjusted R-squared	0.342	0.440	0.557	0.561

Table 4.4: Robustness checks

In columns 1 and 2 we use equity betas as alternative proxies for aggregate exposure of the borrower. In columns 3 and 4 we use total volatility and share of aggregate volatility in total volatility. In columns 5 and 6 we use unlevered equity volatilities. The dependent variable in all specifications is all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$IdioVol^{CAPM}$	91.320***					
	(6.220)					
$Beta^{CAPM}$	-6.890***					
	(2.206)					
$IdioVol^{FF}$		91.226***				
		(6.140)				
$Beta^{MKT}$		-4.663**				
		(2.227)				
$TotalVol$			82.607***	82.352***		
			(6.396)	(6.430)		
$AggVol^{CAPM}/TotalVol$			-64.120***			
			(6.887)			
$AggVol^{FF}/TotalVol$				-72.637***		
				(8.811)		
Unlevered$IdioVol^{CAPM}$					70.517***	
					(8.274)	
Unlevered$AggVol^{CAPM}$					-88.809***	
					(13.533)	
Unlevered$IdioVol^{FF}$						77.391***
						(8.019)
Unlevered$AggVol^{FF}$						-85.602***
						(14.516)
Constant	486.443***	490.052***	499.646***	508.313***	522.334***	523.795***
	(40.229)	(40.339)	(40.588)	(40.419)	(39.942)	(39.711)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,323	11,323	11,323	11,321	11,323	11,321
R-squared	0.563	0.563	0.565	0.566	0.547	0.547

Table 4.5: Panel Regressions

In columns 1 and 2 we run panel regressions with firm fixed effects. In columns 3 and 4 we run panel regressions with bank fixed effects. The dependent variable in the all specifications is all-in-drawn spread. Standard errors are adjusted for clustering at the borrower level in the first two columns and at the lender level in the last two columns and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Firm FE		Bank FE	
	CAPM	Fama French	CAPM	Fama French
	(1)	(2)	(3)	(4)
$IdioVol^{CAPM}$	104.49***		93.14***	
	(8.78)		(7.09)	
$AggVol^{CAPM}$	-47.61**		-49.46***	
	(19.26)		(15.34)	
$IdioVol^{FF}$		106.92***		96.69***
		(9.09)		(6.60)
$AggVol^{FF}$		-35.89*		-42.86**
		(20.21)		(16.57)
Constant	450.41***	453.02***	421.12***	423.61***
	(63.45)	(63.50)	(65.56)	(66.00)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Bank FE	No	No	Yes	Yes
Observations	11,323	11,321	11,323	11,321
Number of Firms	4,192	4,191		
Adjusted R-squared	0.332	0.332	0.494	0.494
Number of Banks			376	376

Table 4.6: Non-bank and Bank Lenders

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Non-bank (1)	Bank (2)	Non-bank (3)	Bank (4)
$IdioVol^{CAPM}$	55.222***	92.687***		
	(11.816)	(5.836)		
$AggVol^{CAPM}$	61.927*	-37.639***		
	(32.641)	(14.035)		
$IdioVol^{FF}$			51.767***	96.310***
			(12.844)	(5.650)
$AggVol^{FF}$			54.521*	-37.376**
			(32.490)	(15.893)
Constant	475.108***	490.106***	477.457***	491.353***
	(97.732)	(43.211)	(96.464)	(43.167)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,796	12,233	1,793	12,231
Adjusted R-squared	0.341	0.541	0.341	0.541

Table 4.7: Prematch propensity score regression and postmatch diagnostic regression

In all specifications, we run Probit regressions. The dependent variable is a dummy for loans originated by non-bank lenders. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Dummy = 1 if the loan is originated by a non-bank lender; 0 if by a bank	
VARIABLES	Prematch	Postmatch
	(1)	(2)
$IdioVol^{CAPM}$	0.933***	-0.004
	(0.100)	(0.140)
$AggVol^{CAPM}$	-0.280	0.099
	(0.284)	(0.394)
LSALES	-0.032	0.029
	(0.030)	(0.043)
LEVERAGE	0.006***	0.000
	(0.001)	(0.002)
PROFMARGIN	0.003***	-0.000
	(0.001)	(0.001)
ROA	-0.018***	-0.000
	(0.004)	(0.006)
NWC	0.000	-0.001
	(0.002)	(0.002)
TANGIBLES	-0.000	-0.000
	(0.001)	(0.001)
MRTBOOK	-0.001***	-0.000
	(0.000)	(0.000)
Constant	-1.948***	-0.551
	(0.437)	(0.798)
Industry Dummies	Yes	Yes
Year Dummies	Yes	Yes
Observations	14,027	3,098
p-value of χ^2	0.000	0.998
Pseudo R2	0.129	0.007

Table 4.8: T-test for equality of means of borrowers' characteristics before and after matching

We compare the sample means of borrowers' characteristics before and after propensity score matching. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Unmatched sample			Matched sample		
Variables	Bank (1)	Nonbank (2)	Difference in means (3)	Bank (4)	Nonbank (5)	Difference in means (6)
$IdioVol^{CAPM}$	0.558	0.820	-0.262***	0.738	0.740	-0.002
$AggVol^{CAPM}$	0.116	0.111	0.004*	0.112	0.114	-0.002
$IdioVol^{FF}$	0.550	0.811	-0.262***	0.729	0.731	-0.002
$AggVol^{FF}$	0.155	0.168	-0.013***	0.165	0.164	0.001
Log(Sales)	5.576	5.101	0.475***	5.064	5.158	-0.094
LEVERAGE	28.159	33.894	-5.735***	31.805	32.611	-0.806
PROFMARGIN	-0.937	-9.762	8.825***	-8.848	-8.925	0.077
ROA	12.108	5.039	7.069***	6.341	6.328	0.013
NWC	21.037	19.003	2.034***	21.118	19.995	1.123
TANGIBLES	69.483	69.894	-0.411	68.629	69.151	-0.522
MKTBOOK	177.004	150.679	26.324***	157.242	155.430	1.812
Observations	12233	1796	14091	1549	1549	3098

Table 4.9: Non-bank and Bank Lenders: A propensity score matched sample

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Non-bank (1)	Bank (2)	Non-bank (3)	Bank (4)
$IdioVol^{CAPM}$	59.867***	94.836***		
	(16.145)	(12.272)		
$AggVol^{CAPM}$	69.523**	-72.335***		
	(35.179)	(22.117)		
$IdioVol^{FF}$			56.536***	100.220***
			(17.048)	(12.292)
$AggVol^{FF}$			62.066*	-66.838***
			(35.245)	(23.753)
Constant	638.863***	443.294***	636.691***	442.001***
	(95.358)	(56.447)	(94.545)	(55.935)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,549	1,549	1,546	1,549
Adjusted R-squared	0.354	0.463	0.354	0.463

Table 4.10: Loan pricing and bank correlation

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Full Sample		Lowly Corr. Banks		Highly Corr. Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$IdioVol^{CAPM}$	88.374***		88.011***		102.139***	
	(9.153)		(8.592)		(11.185)	
$AggVol^{CAPM}$	-12.847		-63.378***		-21.722	
	(17.994)		(20.406)		(16.592)	
$IdioVol^{CAPM} \times LowCorrBK$	14.552*					
	(8.077)					
$AggVol^{CAPM} \times LowCorrBK$	-55.901**					
	(26.457)					
$IdioVol^{FF}$		90.164***		93.192***		105.670***
		(8.523)		(8.965)		(10.348)
$AggVol^{FF}$		-13.441		-63.119***		-25.506
		(19.839)		(23.248)		(17.938)
$IdioVol^{FF} \times LowCorrBK$		18.337**				
		(7.948)				
$AggVol^{FF} \times LowCorrBK$		-52.845**				
		(26.605)				
$LowCorrBK$	2.390	1.982				
	(5.728)	(5.704)				
Constant	495.228***	494.023***	478.592***	478.047***	442.636***	643.520***
	(51.926)	(51.687)	(116.247)	(115.420)	(65.557)	(59.925)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,321	9,319	4,658	4,657	4,663	4,662
Adjusted R-squared	0.572	0.572	0.592	0.592	0.564	0.564

Table 4.11: Loan pricing and bank size

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Full Sample		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$IdioVol^{CAPM}$	106.381***		77.827***		113.753***	
	(7.175)		(6.790)		(9.287)	
$AggVol^{CAPM}$	-14.694		-68.752***		-15.842	
	(17.420)		(15.183)		(16.011)	
$IdioVol^{CAPM} \times SamllBK$	-22.469***					
	(7.944)					
$AggVol^{CAPM} \times SamllBK$	-57.116***					
	(21.621)					
$IdioVol^{FF}$		107.643***		84.200***		115.264***
		(6.843)		(7.205)		(8.834)
$AggVol^{FF}$		-10.540		-70.544***		-12.817
		(19.713)		(16.467)		(19.074)
$IdioVol^{FF} \times SamllBK$		-17.628**				
		(7.847)				
$AggVol^{FF} \times SamllBK$		-60.255***				
		(22.537)				
$SamllBK$	12.830*	12.621*				
	(7.428)	(7.394)				
Constant	506.037***	508.423***	468.019***	471.263***	465.321***	463.777***
	(48.045)	(48.045)	(57.554)	(57.743)	(77.704)	(77.367)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,323	11,321	5,655	5,654	5,668	5,667
Adjusted R-squared	0.562	0.562	0.517	0.517	0.581	0.581

APPENDIX

Table A.1: Data Descriptions and Sources

Variable	Description	Source
LoanSpread	The All-in-Drawn spread is an interest rate spread over LIBOR measured in basis points for each dollar drawn from the loan.	Dealscan
$IdioVol^{CAPM}$	Idiosyncratic volatility using one factor CAPM regressions. Defined as the standard deviation of the residual.	CRSP
$AggVol^{CAPM}$	Systematic volatility using one factor CAPM regressions. Defined as the product of beta and market volatility.	CRSP
$IdioVol^{FF}$	Idiosyncratic volatility from Fama French three-factor model. Defined as the standard deviation of the residual.	CRSP, WRDS
$AggVol^{FF}$	Systematic volatility from Fama French three-factor model. Defined as the total volatility that is attributable to Fama French factors and the factors cross-covariances.	CRSP, WRDS
$Beta^{CAPM}$	Equity beta estimated from the CAPM regression.	CRSP
$Beta^{MKT}$	Coefficient of the market factor estimated from the Fama French three-factor model.	CRSP
$TotalVol$	Total equity volatility, defined as the standard deviation of daily excess return one year before the facility start date.	CRSP
Unlevered$IdioVol^{CAPM}$	Idiosyncratic volatility using one factor CAPM regressions, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP and Compustat
Unlevered$AggVol^{CAPM}$	Systematic volatility using one factor CAPM regressions, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP and Compustat
Unlevered$IdioVol^{FF}$	Idiosyncratic volatility from Fama French three-factor model, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP, WRDS and Compustat
Unlevered$AggVol^{FF}$	Systematic volatility from Fama French three-factor model, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP, WRDS and Compustat
Log(Sales)	Logarithm of firm sales at close of the borrower.	Dealscan
LEVERAGE	Firm leverage defined as sum of long term and short term debts over total assets of the borrower.	Compustat
PROFMARGIN	Profit margin over sales of the borrower.	Compustat
ROA	Return on assets of the borrower.	Compustat
NWC	Net working capital over total assets of the borrower.	Compustat
TANGIBLE	Tangible assets over total assets of the borrower.	Compustat
MRTBOOK	Market to book ratio of the borrower.	Compustat
Log(FacilitySize)	Logarithm of facility amount in million USD.	Dealscan
MATURITY	Maturity of the facility in terms of years	Dealscan
#Lenders	Number of lenders in a tranche of a syndicated loan deal	Dealscan

#Facilities	Number of facilities (tranches) in a syndicated loan deal	Dealscan
REVOLVER	Dummy for lines of credit.	Dealscan
TERMLOAN	Dummy for term loans.	Dealscan
SENIOR	Dummy for senior loans.	Dealscan
SECURED	Dummy for loans with collateral.	Dealscan
Corporate Purpose	Loan purpose dummy indicates loans borrowed for corporate purpose.	Dealscan
Debt Repayment	Loan purpose dummy indicates loans borrowed for debt repayment.	Dealscan
Takeover	Loan purpose dummy indicates loans borrowed for takeover.	Dealscan
Working Capital	Loan purpose dummy indicates loans borrowed for working capital.	Dealscan
Other	Loan purpose dummy indicates loans borrowed for purposes other than the previous four.	Dealscan
SizeBK	Logarithm of bank total assets of the lender.	Call reports, FR Y-9C
SmallBK	Dummy for small banks.	Call reports, FR Y-9C
CapitalBK	Bank equity over total assets of the lender.	Call reports, FR Y-9C
NPLBK	Nonperforming loans over gross loans of the lender.	Call reports, FR Y-9C
ZscoreBK	Bank Z score, defined as sum of equity asset ratio and ROA divided by standard deviation of ROA. We use 8-quarter rolling window when calculating the standard deviation of ROA. We take log transformation as in Laeven and Levine (2009).	Call reports, FR Y-9C
ROABK	Return on assets of the lender.	Call reports, FR Y-9C
LiquidityBK	Liquid assets over total assets of the lender.	Call reports, FR Y-9C
CostOfFundBK	Cost of funds, defined as total interest expenses over total liabilities of the lender.	Call reports, FR Y-9C
LoanGrowthBK	Growth rates of gross loans of the lender.	Call reports, FR Y-9C
InterbankCorr	Interbank correlation, defined as the correlation between bank stock return and S&P 500 bank sector index.	CRSP, Datastream
LowCorrBK	Dummy for less correlated banks of which interbank correlation is below median value.	CRSP, Datastream

Table A.2: Institutional types of non-bank and bank lenders

Lender Types	No. of facilities	No. of borrowers	No. of lenders
Panel A		Non-banks	
Corporation	31	22	17
Finance Company	1,704	930	161
Inst. Invest. Other	8	7	7
Insurance Company	13	8	4
Mutual Fund	1	1	1
Other	25	23	15
Specialty	1	1	1
Trust Company	7	6	3
Total	1,789	984	211
Panel B		Banks	
US Bank	12,130	4,402	567
Thrift or S&L	103	51	7
Total	12,233	4,453	574

Bibliography

Acharya, V. V. (2009): "A theory of systemic risk and design of prudential bank regulation," *Journal of Financial Stability*, 5(3), 224–255.

Acharya, V. V., H. Almeida, and M. Campello (2013): "Aggregate risk and the choice between cash and lines of credit," *The Journal of Finance*, 68(5), 2059–2116.

Acharya, V. V., P. Schnabl, and G. Suarez (2013): "Securitization without risk transfer," *Journal of Financial economics*, 107(3), 515–536.

Acharya, V. V., and T. Yorulmazer (2007): "Too many to fail–An analysis of time-inconsistency in bank closure policies," *Journal of financial intermediation*, 16(1), 1–31.

Affinito, M., and E. Tagliaferri (2010): "Why do (or did?) banks securitize their loans? Evidence from Italy," *Journal of Financial Stability*, 6(4), 189–202.

Agarwal, S., Y. Chang, and A. Yavas (2012): "Adverse selection in mortgage securitization," *Journal of Financial Economics*, 105(3), 640–660.

Agostino, M., and M. Mazzuca (2011): "Empirical investigation of securitisation drivers: the case of Italian banks," *The European Journal of Finance*, 17(8), 623–648.

Albertazzi, U., and L. Gambacorta (2010): "Bank profitability and taxation," *Journal of Banking & Finance*, 34(11), 2801–2810.

Altunbas, Y., L. Gambacorta, and D. Marques-Ibanez (2009): "Securitisation and the bank lending channel," *European Economic Review*, 53(8), 996–1009.

——— (2010): "Bank risk and monetary policy," *Journal of Financial Stability*, 6(3), 121–129.

Ambrose, B. W., M. LaCour-Little, and A. B. Sanders (2005): "Does regulatory capital arbitrage, reputation, or asymmetric information drive securitization?," *Journal of Financial Services Research*, 28(1-3), 113–133.

Arcand, J.-L., E. Berkes, and U. Panizza (2012): "Too much finance?," *International Monetary Fund*.

Arellano, M., and O. Bover (1995): "Another look at the instrumental variable estimation of error-components models," *Journal of econometrics*, 68(1), 29–51.

Bali, T. G., S. J. Brown, and M. O. Caglayan (2012): "Systematic risk and the cross section of hedge fund returns," *Journal of Financial Economics*, 106(1), 114–131.

Bank for International Settlements (2011): *Report on asset securitisation incentives*. Basel Committee on Banking Supervision, Basel, Switzerland.

Bank of England and ECB (2013): *The impaired EU securitization market: causes, roadblocks and how to deal with them*. Bank of England and ECB, Prepared jointly by BoE and ECB for the G20/IMF spring meetings.

Bannier, C. E., and D. N. Hänsel (2008): *Determinants of European banks' engagement in loan securitization*. Deutsche Bundesbank.

Barth, J. R., G. Caprio, and R. Levine (2001): *The regulation and supervision of banks around the world: A new database*. World Bank Publications.

Barth, J. R., G. Caprio Jr, and R. Levine (2013): "Bank Regulation and Supervision in 180 Countries from 1999 to 2011," *Journal of Financial Economic Policy*, 5(2), 111–219.

Beck, T., B. Büyükkarabacak, F. K. Rioja, and N. T. Valev (2012): "Who gets the credit? And does it matter? Household vs. firm lending across countries," *The BE Journal of Macroeconomics*, 12(1).

Beck, T., H. Degryse, and C. Kneer (2014): "Is more finance better? Disentangling intermediation and size effects of financial systems," *Journal of Financial Stability*, 10, 50–64.

Becker, B., and V. Ivashina (2014): "Cyclicality of credit supply: Firm level evidence," *Journal of Monetary Economics*, 62, 76–93.

Benmelech, E., J. Dlugosz, and V. Ivashina (2012): "Securitization without adverse selection: The case of CLOs," *Journal of Financial Economics*, 106(1), 91–113.

Blundell, R., and S. Bond (1998): "Initial conditions and moment restrictions in dynamic panel data models," *Journal of econometrics*, 87(1), 115–143.

Brandao Marques, L., R. Correa, and H. Sapriza (2013): "International evidence on government support and risk taking in the banking sector," .

Cai, J., A. Saunders, and S. Steffen (2011): "Syndication, interconnectedness, and systemic risk," Discussion paper, New York University.

Calomiris, C. W., and J. R. Mason (2004): "Credit card securitization and regulatory arbitrage," *Journal of Financial Services Research*, 26(1), 5–27.

Campbell, J. Y., and G. B. Taksler (2003): "Equity volatility and corporate bond yields," *The Journal of Finance*, 58(6), 2321–2350.

Carbo-Valverde, S., H. Degryse, and F. Rodríguez-Fernández (2015): "The impact of securitization on credit rationing: Empirical evidence," *Journal of Financial Stability*, 20, 36–50.

Cardone-Riportella, C., R. Samaniego-Medina, and A. Trujillo-Ponce (2010): "What drives bank securitisation? The Spanish experience," *Journal of Banking & Finance*, 34(11), 2639–2651.

Carey, M., and G. Nini (2007): "Is the corporate loan market globally integrated? A pricing puzzle," *The Journal of Finance*, 62(6), 2969–3007.

Carey, M., M. Post, and S. A. Sharpe (1998): "Does corporate lending by banks and finance companies differ? Evidence on specialization in private debt contracting," *The Journal of Finance*, 53(3), 845–878.

Carlstrom, C. T., and K. A. Samolyk (1995): "Loan sales as a response to market-based capital constraints," *Journal of Banking & Finance*, 19(3), 627–646.

Casu, B., A. Clare, A. Sarkisyan, and S. Thomas (2013): "Securitization and bank performance," *Journal of Money, Credit and Banking*, 45(8), 1617–1658.

Cebenoyan, A. S., and P. E. Strahan (2004): "Risk management, capital structure and lending at banks," *Journal of Banking & Finance*, 28(1), 19–43.

Cecchetti, S. G., and E. Kharroubi (2015): "Why does financial sector growth crowd out real economic growth?," Discussion paper.

Cerutti, E., S. Claessens, and M. L. Laeven (2015): *The Use and Effectiveness of Macroprudential Policies: New Evidence*, no. 15-61. International Monetary Fund.

Cordella, T., and E. L. Yeyati (2003): "Bank bailouts: moral hazard vs. value effect," *Journal of Financial Intermediation*, 12(4), 300–330.

Dam, L., and M. Koetter (2012): "Bank bailouts and moral hazard: Evidence from Germany," *Review of Financial Studies*, 25(8), 2343–2380.

Demirgüç-Kunt, A., and H. Huizinga (1999): "Determinants of commercial bank interest margins and profitability: some international evidence," *The World Bank Economic Review*, 13(2), 379–408.

Demirgüç-Kunt, A., and H. Huizinga (2001): "The taxation of domestic and foreign banking," *Journal of Public Economics*, 79, 429–453.

Demsetz, R. S. (2000): "Bank loan sales: A new look at the motivations for secondary market activity," *Journal of Financial Research*, 23(2), 197–222.

Dennis, S. A., and D. J. Mullineaux (2000): "Syndicated loans," *Journal of financial intermediation*, 9(4), 404–426.

DeYoung, R., E. Y. Peng, and M. Yan (2013): "Executive compensation and business policy choices at US commercial banks," *Journal of Financial and Quantitative Analysis*, 48(01), 165–196.

Ericsson, J., K. Jacobs, and R. Oviedo (2009): "The determinants of credit default swap premia," *Journal of Financial and Quantitative Analysis*, 44(01), 109–132.

European Central Bank (2011): *Recent developments in securitization.*

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz (2012): "This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis," *The Journal of Finance*, 67(6), 2139–2185.

Fama, E. F., and K. R. French (1993): "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, 33(1), 3–56.

Farhi, E., and J. Tirole (2009): "Collective moral hazard, maturity mismatch and systemic bailouts," Discussion paper, National Bureau of Economic Research.

Focarelli, D., A. F. Pozzolo, and L. Casolaro (2008): "The pricing effect of certification on syndicated loans," *Journal of Monetary Economics*, 55(2), 335–349.

Franke, G., and J. P. Krahnen (2007): "Default risk sharing between banks and markets: the contribution of collateralized debt obligations," in *The Risks of Financial Institutions*, pp. 603–634. University of Chicago Press.

Gadanecz, B., K. Tsatsaronis, and Y. Altunbas (2012): "Spoilt and lazy: the impact of state support on bank behaviour in the international loan market," *International Journal of Central Banking*, 8(4), 121–173.

Gaul, L., and P. Uysal (2013): "Can Equity Volatility Explain the Global Loan Pricing Puzzle?," *Review of Financial Studies*, 26(12), 3225–3265.

Gilje, E., E. Loutskina, and P. Strahan (2013): "Exporting liquidity: Branch banking and financial integration," Working paper, Darden Business School, University of Virginia.

Gong, D., S. Hu, and J. E. Ligthart (2015): "Does corporate income taxation affect securitization? Evidence from OECD banks," *Journal of Financial Services Research*, pp. 1–21.

Gorton, G., and N. Souleles (2007): *Special purpose vehicles and securitization (4th edition)*. University of Chicago Press, Chicago.

Gorton, G. B., and G. G. Pennacchi (1995): "Banks and loan sales marketing nonmarketable assets," *Journal of monetary Economics*, 35(3), 389–411.

Greenbaum, S. I., and A. V. Thakor (1987): "Bank funding modes: Securitization versus deposits," *Journal of Banking & Finance*, 11(3), 379–401.

Gropp, R., C. Gruendl, and A. Guettler (2013): "The Impact of Public Guarantees on Bank Risk-Taking: Evidence from a Natural Experiment," *Review of Finance*, pp. 1–32.

Gropp, R., H. Hakenes, and I. Schnabel (2011): "Competition, risk-shifting, and public bail-out policies," *Review of Financial Studies*, 24(6), 2084–2120.

Han, J., K. Park, and G. Pennacchi (2014): "Corporate taxes and securitization," *The Journal of Finance*, forthcoming.

——— (2015): "Corporate taxes and securitization," *The Journal of Finance*, 70(3), 1287–1321.

Hansen, L. P. (2012): "Challenges in identifying and measuring systemic risk," Discussion paper, National Bureau of Economic Research.

Hertzel, M. G., and M. S. Officer (2012): "Industry contagion in loan spreads," *Journal of Financial Economics*, 103(3), 493–506.

Hirtle, B. (2009): "Credit derivatives and bank credit supply," *Journal of Financial Intermediation*, 18(2), 125–150.

Hoggarth, G., J. Reidhill, and P. J. Sinclair (2004): "On the resolution of banking crises: theory and evidence," Working paper, Bank of England.

Hubbard, R. G., K. N. Kuttner, and D. N. Palia (2002): "Are There Bank Effects in Borrowers' Costs of Funds? Evidence from a Matched Sample of Borrowers and Banks," *The Journal of Business*, 75(4), 559–581.

Huizinga, H. (2004): "The taxation of banking in an integrating Europe," *International Tax and Public Finance*, 11(4), 551–568.

Huizinga, H., J. Voget, and W. Wagner (2014): "International Taxation and Cross-Border Banking," *American Economic Journals: Economic Policy*, forthcoming.

International Monetary Fund (2010): *A fair and substantial contribution by the financial sector: Final report for the G-20*. International Monetary Fund, Washington, D.C.

Ivashina, V. (2009): "Asymmetric information effects on loan spreads," *Journal of Financial Economics*, 92(2), 300–319.

Ivashina, V., and Z. Sun (2011): "Institutional demand pressure and the cost of corporate loans," *Journal of Financial Economics*, 99(3), 500–522.

James, C., and A. Kizilaslan (2014): "Asset Specificity, Industry-Driven Recovery Risk, and Loan Pricing," *Journal of Financial and Quantitative Analysis*, 49(03), 599–631.

Jones, D. (2000): "Emerging problems with the Basel Capital Accord: Regulatory capital arbitrage and related issues," *Journal of Banking & Finance*, 24(1), 35–58.

Kaufmann, D., A. Kraay, and M. Mastruzzi (2011): "The worldwide governance indicators: methodology and analytical issues," *Hague Journal on the Rule of Law*, 3(02), 220–246.

Keeley, M. C. (1990): "Deposit insurance, risk, and market power in banking," *American economic review*, 80(5), 1183–1200.

Keen, M. (2011): "Rethinking the taxation of the financial sector," *CESifo Economic Studies*, 57(1), 1–24.

Keys, B., T. Mukherjee, A. Seru, and V. Vig (2010a): "Did securitization lead to lax screening? Evidence from subprime loans," *The Quarterly Journal of Economics*, 125(1), 307–362.

KEYS, B. J., T. K. MUKHERJEE, A. SERU, AND V. VIG (2010b): "Did securitization lead to lax screening? Evidence from subprime loans," *The Quarterly Journal of Economics*, 125(1), 307–362.

KEYS, B. J., A. SERU, AND V. VIG (2012): "Lender screening and the role of securitization: evidence from prime and subprime mortgage markets," *Review of Financial Studies*, 25, 2071–2108.

KING, R. G., AND R. LEVINE (1993): "Finance and growth: Schumpeter might be right," *The Quarterly Journal of Economics*, pp. 717–737.

LAEVEN, L., AND R. LEVINE (2009): "Bank governance, regulation and risk taking," *Journal of Financial Economics*, 93(2), 259–275.

LAEVEN, L., AND F. VALENCIA (2013): "Systemic banking crises database," *IMF Economic Review*, 61(2), 225–270.

LANGFIELD, S., AND M. PAGANO (2014): "Bank bias in Europe: Effects on systemic risk and growth," Discussion paper, Working paper.

LEMMON, M., L. X. LIU, M. Q. MAO, AND G. NINI (2014): "Securitization and capital structure in nonfinancial firms: An empirical investigation," *The Journal of Finance*, 69(4), 1787–1825.

LEVINE, R. (2005): "Finance and growth: theory and evidence," *Handbook of economic growth*, 1, 865–934.

LIN, H., AND D. PARAVISINI (2013): "The effect of financing constraints on risk," *Review of Finance*, 17(1), 229–259.

LOAYZA, N. V., AND R. RANCIERE (2006): "Financial development, financial fragility, and growth," *Journal of Money, Credit and Banking*, pp. 1051–1076.

LOUTSKINA, E. (2011): "The role of securitization in bank liquidity and funding management," *Journal of Financial Economics*, 100(3), 663–684.

LOUTSKINA, E., AND P. E. STRAHAN (2009): "Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations," *The Journal of Finance*, 64(2), 861–889.

MADDALONI, A., AND J.-L. PEYDRÓ (2011): "Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the Euro-area and the US lending standards," *Review of Financial Studies*, 24(6), 2121–2165.

MARSH, I. W. (2006): "The effect of lenders' credit risk transfer activities on borrowing firms' equity returns," *Cass Business School Research Paper*.

MERTON, R. C. (1974): "On the pricing of corporate debt: The risk structure of interest rates," *The Journal of Finance*, 29(2), 449–470.

——— (1977): "An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory," *Journal of Banking & Finance*, 1(1), 3–11.

Mills, E. S. (1987): "Has the United States overinvested in housing?," *Real Estate Economics*, 15(1), 601–616.

Morgan, D. P. (2002): "Rating banks: Risk and uncertainty in an opaque industry," *American Economic Review*, 92, 874–888.

Nadauld, T. D., and M. S. Weisbach (2012): "Did securitization affect the cost of corporate debt?," *Journal of financial economics*, 105(2), 332–352.

Nijskens, R., and W. Wagner (2011): "Credit risk transfer activities and systemic risk: How banks became less risky individually but posed greater risks to the financial system at the same time," *Journal of Banking & Finance*, 35(6), 1391–1398.

Norden, L., C. S. Buston, and W. Wagner (2014): "Financial innovation and bank behavior: Evidence from credit markets," *Journal of Economic Dynamics and Control*, 43, 130–145.

Panetta, F., and A. Pozzolo (2010a): "Why do banks securitize their assets? Bank-level evidence from over one hundred countries," Working paper, Banca d'Italia.

Panetta, F., and A. F. Pozzolo (2010b): "Why do banks securitize their assets? Bank-level evidence from over one hundred countries," *Bank-Level Evidence from Over One Hundred Countries (March 16, 2010)*.

Pavel, C., and D. Phillis (1987): "Why commercial banks sell loans: An empirical analysis," *Federal Reserve Bank of Chicago Economic Perspectives*, 14, 3–14.

Peersman, G., and W. Wagner (2014): "Shocks to Bank Lending, Risk-Taking, Securitization, and Their Role for US Business Cycle Fluctuations," .

Pennacchi, G. G. (1988): "Loan sales and the cost of bank capital," *The Journal of Finance*, 43(2), 375–396.

Purnanandam, A. (2011): "Originate-to-distribute model and the subprime mortgage crisis," *Review of Financial Studies*, 24(6), 1881–1915.

Santos, J. A. (2011): "Bank corporate loan pricing following the subprime crisis," *Review of Financial Studies*, 24(6), 1916–1943.

Santos, J. A., and A. Winton (2008): "Bank loans, bonds, and information monopolies across the business cycle," *The Journal of Finance*, 63(3), 1315–1359.

——— (2013): "Bank capital, borrower power, and loan rates," Discussion paper, NY Fed and University of Minnesota.

Sassi, S., and A. Gasmi (2014): "The effect of enterprise and household credit on economic growth: New evidence from European union countries," *Journal of Macroeconomics*, 39, 226–231.

Shaviro, D. (2011): "The 2008 financial crisis: Implications for income tax reform," Working paper, NYU Law and Economics.

Stein, J. C. (2010): "Securitization, shadow banking & financial fragility," *Daedalus*, 139(4), 41–51.

Strahan, P. E. (1999): "Borrower risk and the price and nonprice terms of bank loans," *FRB of New York Staff Report*, (90).

Sufi, A. (2007): "Information asymmetry and financing arrangements: Evidence from syndicated loans," *The Journal of Finance*, 62(2), 629–668.

Tucker, J. W. (2010): "Selection bias and econometric remedies in accounting and finance research," *Journal of Accounting Literature, Winter*.

Vives, X. (2011): "Competition policy in banking," *Oxford Review of Economic Policy*, 27(3), 479–497.

Zhang, B. Y., H. Zhou, and H. Zhu (2009): "Explaining credit default swap spreads with the equity volatility and jump risks of individual firms," *Review of Financial Studies*, 22(12), 5099–5131.