Essays on Banking and Corporate Finance

Chala, Alemu Tulu

2017

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

Link to publication

Citation for published version (APA):
Chala, A. T. (2017). *Essays on Banking and Corporate Finance*. [Doctoral Thesis (compilation), Department of Economics]. Lund University.

Total number of authors:
1

Essays on Banking and Corporate Finance

Alemu Tulu Chala

DOCTORAL DISSERTATION

By due permission of the School of Economics and Management,

Lund University, Sweden.

To be defended at Holger Crafoord EC3:108, Lund

on November 13, 2017 at 10:15.

Faculty opponent

João A.C. Santos, Vice President and Function Head

Financial Intermediation Function, Federal Reserve

Bank of New York

Organization Lund University Department of Economics P.O. Box 7082 S-220 07 Lund, Sweden	**Document name** Doctoral dissertation **Date of issue** November 13, 2017
	CODEN: ISSN 0460-0029
Author Alemu Tulu Chala	**Sponsoring organization**

Title and subtitle
Essays on Banking and Corporate Finance

Abstract

This doctoral dissertation comprises three independent essays on banking and corporate finance. The essays are preceded by an introduction to the thesis. The first essay explores whether refinancing risk is an important determinant of debt-maturity decisions. To this end, it investigates how firms with refinancing risk choose the maturity of new loans they obtain during the 2007–2009 financial crisis. The firms' refinancing risk is measured by the maturing portion of outstanding long-term debt. The result shows that firms with a high refinancing risk choose longer maturities.

The second essay examines the association between a lead arranger's relationship with a firm and its retained share in the loan to that firms. While some literature indicates that lending relationships can help to alleviate ex post agency conflicts, others imply that relationship lead arrangers may use their information advantage to exploit syndicate participants. Using syndicated loans made to U.S. firms, this article shows that lead arrangers retain a smaller share in lending relationships with firms.

The third essay (co-authored with Jens Forssbæck) examines the relationship between collateral and credit rationing. In theory, the use of collateral in credit contracting should mitigate the information problems that are widely held to be the primary cause of credit rationing. However, direct empirical evidence on this link is scant. Using survey data that provides clean measures of quantity and loan size rationing, our results suggest that collateral reduces the likelihood of experiencing loan-size credit rationing.

Keywords
Refinancing Risk, Debt Maturity, Financial Crisis, Syndicated Lending, Relationships, Retained Share, Loan-size Rationing, Collateral

Classification system and/or index terms (if any)

Supplementary bibliographical information	**Language** English
ISSN and key title 0460-0029 Lund Economic Studies no. 207	**ISBN** 978-91-7753-450-1 (print) 978-91-7753-451-8 (pdf)

Recipient's notes	**Number of pages 220**	**Price**
	Security classification	

Distributed by Department of Economics, P.O. Box 7082, S-220 07 Lund, Sweden

Signature Alemu Tulu Chala Date 2017-09-28

Essays on Banking and Corporate Finance

Alemu Tulu Chala

Lund University

Lund Economic Studies Number 207

Distributed by the Department of Economics
Lund University
P.O. Box 7082
S-220 07 Lund
SWEDEN

ISBN 978-91-7753-450-1 (print)
ISBN 978-91-7753-451-8 (pdf)
ISSN 0460-0029

Printed in Sweden by Media-Tryck, Lund University
Lund 2017

Dedicated to my father

Contents

Acknowledgements

Essays on Banking and Corporate Finance represents the culmination of my doctoral studies at Lund University over 2011–2017. During the course of my research, I have received much advice and unflinching support from many quarters in countless ways. When I take inventory of where I have come from, I cannot help but appreciate those who have helped me get here and, as a result, influenced the course of my life. I was about nine years old and in Grade 3 and I lived in deep poverty. I fainted from hunger and even walked on four legs like an animal as my feet were too weak to hold me up from not eating for days. In the fifth grade, I was absent from school for two weeks because my family could not afford to buy me a pen. As it became impossible to continue studying, I dropped out of school at Grade 6 until, unexpectedly, I resumed my studies two years later. The completion of this doctoral dissertation marks the end of another chapter in my life, and I owe so much to the wonderful people who have helped me come this far. A brief account of their generous contributions would better express my feeling of deep gratitude; simply saying "Thank you" to them would be shabby.

Chief among these people is my main supervisor Jerker Holm, who assumed the role of the supervisor after Ola Bengtsson suddenly passed away. Jerker has shown great commitment to the supervision process, which has involved numerous conversations, regular meetings and in-depth discussions throughout my doctoral studies; I feel I was best served by his precise guidance; he has done everything so that I could successfully navigate the dissertation process. Without his excellent ideas, this thesis would have been a very different manuscript. I have been impressed by how much time and effort he has been wiling to spend proofreading my research papers. Without his forensic surveillance of my academic writing, this dissertation would have been a far poorer manuscript. During the course of this research work, on countless occasions, I found myself scrapping what I had done and starting to write all over again, only to discard it again. In deadline-driven academia, he has been immensely patient with me.

Besides academic advice, Jerker has also been generously supportive and immensely helpful throughout an incredibly challenging time. I was racked by anxieties and stress that could have blown my life off course, but I trudged forth with the indispensable help of my advisors. Apart from a constant source of encouragement, Jerker has offered his help through deeds: He went beyond his duties and facilitated meetings so that I could receive essential support. Without his help, it is difficult to imagine coming this distance and this thesis would not have seen the light of day. I could not have asked for a better advisor and can never thank Jerker enough for his help.

I also owe a tremendous debt of gratitude to my assistant supervisor Jens Forssbæck. Many of my comments about Jerker also apply to Jens: insightful conversations, constructive comments, proofreading manuscripts, patience and generous encouragement during challenging times. Jens is also a coauthor of the third essay of this thesis. I am honored to have worked with him and he has taught me the art of being methodic in problem solving. I have been astonished by his willingness to go into the office on weekends while writing the draft version of our paper. He has been essential to the completion of this thesis and without his involvement this thesis would have taken a very different shape.

It would be very remiss of me not to acknowledge Ola Bengtsson who guided me with invaluable advice during the early phase of this research. Ola was not only a person of luminous intellect, he was also very supportive. He often encouraged me to have research chats with visiting scholars. Above all, what I cannot forget is that he wrote me an email that he would continue advising me while on his deathbed. His memory will live on.

Other individuals with whom I have had the privilege of engaging have also provided invaluable comments that greatly improved the quality of this doctoral manuscript. Erik von Schedvin from Sveriges Riksbank and a discussant during my final seminar, offered truly fruitful discussions, especially regarding the method used in the first essay. Jaokim Bang from UNSW Australia, a discussant at the Fourth National PhD Workshop in Finance at ShoF, provided valuable comments on the second essay. Mariasunta Gianneti from the Stockholm School of Economics was willing to comment on an early draft of first essay. I extend warm gratitude to them all.

A number of people, while not directly engaged in the production of this doctoral thesis, have nonetheless been very helpful during the course of this research. I am much indebted to Fredrik Sjöholm, who was the head of the Department of Economics, for providing emotional support during challenging times. I am also grateful to Tommy Andersson, coordinator of PhD program, for helpful suggestions on how best to proceed with my research work during those difficult times. The support I have received from a number of individuals from the community outside of the department has been indispensable for the completion of this thesis. I am immensely grateful to all of them. These individuals include Mikael Nornholm, René Svensson, Ingrid Ekelund, Emma Bergkvist and Linnéa Wallenberg. Linnéa, I owe a huge debt of gratitude to you.

Other academics at the department deserve thanks for helpful ideas, thoughts and their contributions to my professional education: David Edgerton, Frederik Lundtofte, Hossein Asgharian, Peter Jochumzen, Birger Nilsson, Anders Vilhelmsson, Hans Byström, Martin Strieborny, and others. Osmis Habte deserves my sincerest thanks for being a nice office mate. I have also benefited from conversations with former and present PhD students: Milda Norkute, Mahtemeab Tadesse, Valeriia Dzhamalova, Hassan Sabzevari, Aron Berg, Dinh-Vinh Vo, Björn Thor Anarson, Usman Khalid, Karl Mc Shane, Sara Moricz, Mehmet Caglar Kaya, Bo Larsson, Fredrik Said Madsen, Dominice Goodwin, Jim Ingebretsen Carlson, Jörgen Kratz and Pol Campos Mercade. I thank you all. My gratitude also goes to administrative staffs who have been very helpful throughout my PhD studies. I would like to mention in particular Jenny Lindström Wate, Nathalie Stenbeck, Mariana Anton, Rikke Barth'elemy, Karin Wander, Anna Marciniak and Marie Pihl.

I would also like to record my thanks to João A. C. Santos, who is a Vice President and Head of the Financial Intermediation Function at the Federal Reserve Bank of New York, for having graciously agreed to be my faculty opponent. Thanks also go to the members of the grading committee for being willing to read this manuscript. I would like to extend my special appreciation to Katarina Juselius of University of Copenhagen for writing me a recommendation letter when I decided to apply for the PhD program at Lund University. John Morris deserves thanks for his careful editing.

The process associated with this doctoral dissertation drew me away from my family. They have been very supportive, understanding, and incredibly patient. They have given me unquestioned affection. My wife Genet has stood by my side during the very long period of doing research and has been a gracious pillar of support in many respects, from enduring a life apart during the first year of my PhD studies, to accompanying me to Sweden, to bringing forth our son during my doctoral work, to willingly caring for our children, to picking them up from kindergarten and school, and to being inexhaustibly tolerant. You scarified yourself so that I concentrate on my PhD studies. Geni, I can never thank you enough. To our children, Deborah (7) and Adonijah (4), who light up our home: I know, you have dearly missed me, and I you. Deborah, when you grow up, you will understand why you have said "papa is always working." I wish to thank both of you for being patient and promise I will try to become a more attentive father.

Lund, Sweden, 28 September 2017
ALEMU TULU CHALA

Introduction

1 Introduction

Credit-supply disruptions, within-syndicate conflicts and credit rationing have been the focus of considerable research. Disruptions to the supply of credit can emanate from a financial crisis (Mishkin, 1992, 1999), which dries up liquidity in the market for loanable funds (Brunnermeier, 2009), making financial intermediaries unable to raise and provide liquidity to firms. Conflicts within lending syndicates can stem from information asymmetries between lead arrangers and participants, which may impede fund pooling across lenders within a syndicate group (Sufi, 2007). The rationing of credit to borrowers can originate from information asymmetries between lenders and borrowers (Stiglitz and Weiss, 1981), which may prevent the debt market from functioning according to the competitive principle. Although we have learned a great deal from the existing research, we still have much to learn about many issues related to these topics; this dissertation addresses three issues.

The first issue is associated with the relationship between refinancing risk—the risk of being unable to refinance maturing debt at reasonable interest rates—and firms' debt maturity choices. Spurred by the financial crisis of 2007–2009, the issue of refinancing has attracted a good deal of scholarly attention in recent years. The crisis has shown that shortening maturity can expose firms to refinancing risk (Brunnermeier, 2009) and a recent stream of theoretical work is exploring the extent of that exposure (He and Xiong, 012a,b; Morris and Shin, 2016; Seta et al., 2016); the research also investigates the important role of refinancing-risk considerations in the choice of shorter versus longer maturities (Segura and Suarez, 2011; Cheng and Milbradt, 2012; Szkup, 2013; He and Milbradt, 2016). In fact, the notion that refinancing risk is an important factor to consider in debt-maturity decisions is not a new idea; the theoretical work has long recognized the significance of refinancing-risk considerations in debt-maturity choices (Diamond, 1991a).

Recent theoretical work incorporating refinancing risk into debt-maturity-choice models advances perspectives underpinning the argument that longer maturities may reduce firms' exposure to future refinancing risk. For example, Cheng and Milbradt (2012) and He and Xiong (012b) argue that longer maturities allow firms to disperse debt expiration dates. Later work by He and Milbradt (2016) suggests that the issuance of new debt with longer maturities enable firms to lengthen the maturity structure of their overall debt. Along these same lines, exposure to refinancing risk increases exponentially with shorter maturities (Jun and Jen, 2003, p. 11). Despite these theoretical efforts and episodes of severe disruption in credit supply (Ivashina and Scharfstein, 2010), heightened risk of fire sales (Brunnermeier and Yogo, 2009; Shleifer and Vishny, 2011) and missed profitable investments (Duchin et al., 2010; Almeida et al., 2012), we know little about how firms choose debt maturity in the presence of refinancing risk. Although the financial crisis in recent years has reintroduced the importance of refinancing risk for maturity choice, the empirical research remains in its infancy. The current thesis addresses this gap in the empirical literature by investigating whether refinancing-risk considerations positively affect debt maturity.

The second issue pertains to the effect of lending relationships on loan syndication structures. Syndicated lending—an arrangement whereby a consortium of lenders advances funds jointly to a single firm—has attracted increasing attention in the banking literature. One reason for this interest has to do with the fact that such a multi-lender financing arrangement has become the most important source of firms' external financing (Dennis and Mullineaux, 2000; Chui et al., 2010). A prominent feature of this financing arrangement is that one or more of the lenders function as lead arranger and the others are participants. Lead arrangers oftentimes maintain lending relationships with the borrowing firms (Bharath et al., 2007), enabling them to collect soft information and, consequently, hold some degree of information monopoly about their borrowers. Because participants are primarily involved in an arm's-length, transaction-based lending, the potential information asymmetry has raised a debate over whether agency conflicts within lending syndicates hamper loan syndication activities (Panyagometh and Roberts, 2010). Here the most important question is whether such information asymmetry reduces participants' loan supply.

The literature offers conflicting perspectives regarding the impact of lead arrangers' lender–borrower relationships on their syndication activities. A large literature argues that learning through the process of lending reduces costs of producing firm-specific information (Haubrich, 1989; Boot, 2000). This suggests that lead arrangers with prior relationships enjoy a monitoring cost advantage, encouraging participants to buy more of the loans. On the other hand, the banking literature has often suggested that lenders do not share proprietary information about their clients with competing lenders (Sharpe, 1990; Rajan, 1992). In the context of syndicated lending, this may suggest that participants may lack information that lead arrangers have about the quality of the loan. To the extent that participating lenders imperfectly observe the lead arranger's screening and monitoring activities, they require lead arrangers with relationships (who presumably have superior information) to retain more of the loan to protect themselves from information exploitation. Because relationships can potentially have opposite effects on retained shares, this link will have to be established empirically, defining the purpose of the second essay of this thesis.

The third issue is associated with the relationship between collateral pledging and credit rationing in the markets for small business loans. The concept of credit rationing is the subject of an extensive body of theoretical literature. Credit rationing's important implications for the supply of credit justify this considerable attention, both from an earlier strand of literature explaining credit rationing by the risk of default (Hodgman, 1960; Freimer and Gordon, 1965) and a later strand of literature attributing credit rationing to information asymmetries (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). The rationing of credit is generally thought to be a major concern for small firms. The availability of credit may matter most to them for two reasons: First, small firms are informationally opaque. Second, they depend largely on banks for their external financing (Berger and Udell, 1995).

A common theme of the theoretical work on credit rationing is that a mechanism that mitigates credit-market imperfections lowers the hurdle of access to external financing; this has led to the development of a set of collateral theories. One strand of the theoretical literature motivates collateral as a screening device, reducing ex ante private information that may lead to adverse selection (Bester, 1985; Chan and Kanatas, 1985; Besanko and Thakor, 1987). Another strand motivates collateral as a commitment device, constraining firms' inherent predisposition toward risk shifting (Chan and Thakor, 1987; Boot and Thakor, 1994), reduced effort (Watson, 1984; Innes, 1990) and strategic default (Benjamin, 1978; Hess, 1985). Thus, there is much to suggest a negative link between collateral use and credit rationing. If collateral could be shown to reduce credit rationing, it would have important implications for small firms' access to credit. However, while the theoretical study of collateral's role in alleviating credit rationing has a long history, it is telling that the available evidence to date is limited and predominantly indirect. Empirically establishing the effect of collateral on credit rationing to provide direct evidence on this issue essentially defines the goal of the third essay of this thesis.

1 WHAT WE KNOW AND DO NOT KNOW

Refinancing-risk exposure is widely expected to increase considerably in times of financial crisis. A stream of early theoretical literature provides models of a financial crisis precipitated by banking panics due to depositor runs. They motivate runs by relying on depositors' self-fulfilling beliefs about the actions of other depositors due to a coordination failure (Diamond and Dybvig, 1983; Postlewaite and Vives, 1987) and depositors' asymmetric information about bank fundamentals (Chari and Jagannathan, 1988; Jacklin and Bhattacharya, 1988). However, little evidence suggests a very classic run was at work during the recent financial crisis (Shin, 2009). Rather, recent studies document that a new-fashioned run was at work: financial institutions' runs on other financial intermediaries. Such runs occurred in the interbank (repo) markets (Gorton and Metrick, 2012), in the asset-backed commercial-paper market (Covitz et al., 2013) and on money-market funds (Schmidt et al., 2016). The freezes of trading in these markets dried up liquidity, triggering a sharp disruption in bank lending and generating refinancing risk for firms. It is generally agreed that firms are exposed to refinancing risk through their debt's maturity structure. As such, distributing maturity dates may be their major concern.

However, it is less clear whether firms respond to refinancing risk by adjusting (i.e., lengthening) their maturity structures, mainly because maturity decisions normally involves trade-offs: Firms weigh the concern for alleviating agency conflicts against that for mitigating refinancing risk. A fairly extensive and long-standing strand of the debt-maturity-choice literature suggests that shorter maturity may help lower debt's agency costs by mitigating the problem of asset substitution (Jensen and Meckling, 1976; Barnea et al., 1980) and underinvestment (Myers, 1977; Stulz and Johnson, 1985), aligning shareholder and manager interests (Grossman and Hart, 1982) and alleviating the misvaluation of debt (Flannery, 1986). This raises the question of whether refinancing risk concern can dominate those of agency conflicts (Mian and Santos, 2011; Xu, 2016). However, an important question remains: Do firms with refinancing risk display, as theory suggests, maturity-lengthening behavior during crisis times? It has already been shown that lenders tighten lending standards in periods of crisis (Campello et al., 2011). Other studies have also shown that bank-dependent firms are likely to suffer most from negative shocks experienced by the banking sector (Chava and Purnanandam, 2011). Yet, little is known about how debt-maturity response in anticipation of refinancing risk may vary among firms classified on the basis of their access to capital markets.

Early studies of syndicated lending advanced a variety of theoretical perspectives underpinning why lenders form a team with the intent of jointly loaning to a firm. Perhaps the most well known of these theories is the risk-diversification theory (Wilson, 1968; Amershi and Stoeckenius, 1983). This theory emphasizes that syndication allows risk sharing across a group of lenders reducing syndicate-lending members' individual exposure to the risks. Other theories offer alternative rationales, such as emphasizing the role of syndication in helping financial intermediaries comply with capital-adequacy requirements and lending limits (for empirical evidence, see Simons, 1993; Lockett and Wright, 2001; Brander et al., 2002; Jones et al., 2005). The syndication process may, however, erode lead arrangers' screening and monitoring incentives and, consequently, may generate intersyndicate agency conflicts.

To align the potentially diverging interests between lead arrangers and participating lenders, syndicates are generally structured to require the lead arrangers to have "skin in the game." Such financial stakes in the loans are widely shown to depend on the degree of the informational wedge between the lead arranger and the participating lenders. For example, Jones et al. (2005) show that when the borrowing firms are informationally transparent, lead arrangers sell more of the loans. In contrast, Sufi (2007) shows that when borrowers are informationally opaque, lead arrangers must hold more of the loans. This research thus suggests that the fraction of loans retained by lead arrangers typically reflects the incentive level required to induce diligent screening and monitoring.

While numerous empirical studies examine the linkage between a lending relationship and syndicated-contract terms, the practical importance of relationships on retained shares is not well understood. Lead arrangers' desire to protect their reputations—in accordance with the perspective advanced by Diamond (1989, 1991b) and others—can noncontractually rein in lead arrangers' agency problems (Sufi, 2007; Ivashina, 2009; Ross, 2010). The implication is pretty clear: Reputable lead arrangers do not need to hold large financial stakes to be motivated to undertake duly diligent screening and monitoring. However, little is known, if any, about how the impact of relationships varies with lead arrangers' reputations. The literature also maintains that syndicated loan contracts incorporate covenants to help mitigate lead arranger–participant conflicts (Dass et al., 2011), as well as to help curb the very classic borrower–lender agency conflicts (Smith and Warner, 1979). This raises the important question of whether the effect of relationships on the retained share varies between covenanted and uncovenanted loans.

Theoretical models of credit rationing have introduced at least two principal concepts with important implications for how credit rationing is measured empirically. The type of credit rationing that Jaffee and Russell (1976), Gale and Hellwig (1985), Schreft and Villamil (1992) and Kjenstad et al. (2015) consider is identified as *loan-size rationing* and denotes an unsatisfied demand for credit at the prevailing loan rate—i.e., the amount offered is smaller than the loan size firms would like to receive. The literature represented by Stiglitz and Weiss (1981) and Williamson (1986) analyzes *quantity rationing*, a phenomenon whereby some borrowers obtain loans while others do not. For the most part, empirical studies have offered support for the information-based rationale of credit rationing (Berger and Udell, 1992), and a number of studies, particularly those that use survey data, have paid considerable attention to quantity rationing (Chakravarty and Yilmazer, 2009; Drakos and Giannakopoulos, 2011). It is important to note that in a situation where a loan application is rejected (i.e., quantity rationing), collateral is unavailable for the simple reason that no transaction ever take place. Though loan-size rationing has received little attention in the empirical literature, it is appealing because it defines which other contract terms (including collateral) are observed.

Although collateral has traditionally been the center of attention in the credit-rationing literature, much of the empirical work has focused on examining collateral-pledging motivations. Studies of the relationship between information asymmetries and the incidence of collateral offer a good example. These papers examine the signaling role of collateral, in that whether a reduction in ex ante information asymmetries leads to a lower incidence of collateral. The result of this sort is found in Berger et al. (2011). Other studies on the relationship between incentive problems and collateral pledging offer another example of the empirical approach usually employed. This strand of literature examines whether collateral can have a disciplinary effect. Results of this sort are found in Machauer and Weber (1998) and Jiménez et al. (2006). Although the results of these studies are consistent with the theoretical literature on the role of collateral, they are only suggestive and do not necessarily provide sufficient evidence of the negative link between collateral and credit rationing. A few studies stand out because of their attempt to provide direct evidence on the impact of collateral (Ogawa and Suzuki, 2000; Carbo-Valverde et al., 2015; Cerqueiro et al., 2016). However, these studies use land assets as a proxy for collateral, securitization and legal changes to collateral, respectively, and do not employ the pledged collateral at the time of loan origination, as the third essay of this thesis does. Moreover, it is also unclear whether collateral has an important role to play in the presence of other mechanisms such as relationships that help mitigate information asymmetries, and that may provide a substitute (or complement) for collateral.

2 A REVIEW OF CONTRIBUTIONS

This dissertation comprises three independent essays dealing with issues in banking and corporate finance. The first essay, "Refinancing risk and debt maturity choice during a financial crisis," contributes to the literature on debt-maturity choice by empirically identifying whether refinancing-risk considerations are an important determinant of debt-maturity decisions. To this end, the essay focuses specifically on the relationship between firms' exposure to refinancing risk and the maturity of new loans they issue during the 2007–2009 financial crisis.

The estimation is based on loans originated in the United States between August 2007 and June 2009 according to data from the Dealscan database. The financial information of the borrowing firms is extracted from the Compustat dataset and is then matched and merged with the loan dataset. Using the firms' precrisis information on the maturity structure of long-term debt, this essay constructs a predetermined measure of refinancing risk. More specifically, it employs the maturing portion of long-term debt outstanding in year 2003 and 2004 that comes due during the financial crisis. This has the advantage of greatly reducing concerns about endogeneity of the outstanding long-term debt's maturity structure.

The result provides evidence that refinancing risk is positively and significantly associated with the debt's maturity. This shows that firms with refinancing risk choose longer maturity during the crisis. That is, firms with a higher portion of maturing long-term debt are more likely to issue new loans of longer maturity. This positive relationship is consistent with the theoretical prediction that firms with a higher potential for exposure to refinancing risk choose longer maturity to mitigate their exposure to refinancing risk. The negative relationship observed during the precrisis period—when refinancing risk is less substantial because of the availability of cheap credit (Keys et al., 2010; Chava and Purnanandam, 2011)—rejects the alternative interpretation that the observed positive link reflects a routine maturity-choice pattern in which firms replace maturing long-term debt with new loans of longer maturity.

The essay offers several extensions to the baseline result. One shows that the impact of refinancing risk on debt maturity is more pronounced for speculative-grade firms. This finding can be understood in light of the previous evidence that firms with limited access to public debt markets are the most affected by the crisis and, as such, display strong refinancing-risk concerns. Another extension shows that the maturity effect of refinancing risk is stronger for firms with low cash flows. The third extension appears to provide evidence that relationship lenders help their borrowers with refinancing risk by providing longer maturity loans during the crisis. To alleviate concerns related to sample-selection bias, this essay employs matching-estimation methods; the results suggest that the baseline result is robust to this alternative estimation technique.

The second essay, "Syndicated lending: The role of relationships for the retained share," contributes to the syndicated-lending literature by analyzing how lead arranger–firm relationships affect the shares retained by lead arrangers. The analysis uses syndicated loans made to nonfinancial U.S. firms over the period from 1987 to 2013 based on information extracted from the Dealscan database. This information is matched and merged with the borrowers' financial information extracted from the Compustat dataset. Relationship is measured by tracking the History of lending interactions and identifying whether there exists (and the number of) interactions in the preceding years.

The analysis provides evidence that relationships are significantly negatively related to the share retained by lead arrangers. This result suggests that building lending relationships with borrowers helps lead arrangers retain a smaller share of the loans that they syndicate. On the basis of this result, one can conclude that a lending relationship's agency-conflict-alleviating nature outweighs its information-exploitation-facilitating feature in the syndicated-loan market. Consequently, a syndicate's participating lenders do not require relationship lead arrangers to retain a higher portion of syndicated loans to mitigate the dilution of screening and monitoring incentives arising from syndication and delegation.

The analysis offers several extensions to the baseline results. First, the analysis shows that the reduction in the retained share is more pronounced in syndicate arrangements headed by less reputable lead arrangers. This finding can be understood in light of the theory of corporate reputation: Reputable lead arrangers are expected to fend off the temptation to become lenient in their screening and monitoring tasks, and such self-restricting behavior makes the importance of relationships less relevant for them. Second, the analysis documents that the effect of lending relationship on the retained share is more pronounced in loan contracts that include covenants, perhaps because covenanted loans require closer monitoring and hence the benefit of relationships. Finally, exploiting the distance between the lead arranger's and borrower's headquarters—to address any potential heterogeneity concerns with relationship formation—the analysis shows that the result remains robust to several alternative estimation techniques.

The third essay, "Does collateral reduce loan-size credit rationing? Survey evidence" coauthored with Jens Forssbæck, contributes to the literature on credit rationing and collateral. The analysis focuses on loan-size rationing, whereby the granted amount is less than the amount requested. The estimation is based on survey data drawn from the Survey of Small Business Finance (SSBF) conducted by the Federal Reserve Board. This rich data set contains extensive information about the loan application and approval processes and provides a clean measure of loan-size rationing. We pool across the 1993, 1998 and 2003 versions of the survey. This survey allows us to model the entire loan application and approval process.

This essay uses a methodology different from that of prior empirical studies: The model is estimated in two parts. Our basic premise is that credit demand, the firm's decision about whether to apply, and the lender's decision regarding whether to grant the loan are interdependent. Therefore, the first part employs a trivariate probit model to jointly estimate a three-step sequential-selection model: The first equation predicts credit demand (firms decide whether they need credit); the second equation predicts loan application (conditional on credit demand, firms decide whether to request a loan); and the third equation predicts loan approval (given a firm's credit demand and application decision, lenders decide whether to approve the loan application). Consistent with the assumption, the finding provides evidence that these outcomes are a sequence of interconnected decisions.

In the second part, the method of instrumental variables (IV) is used to estimate the impact of collateral on credit rationing. This method treats collateral and interest rates as endogenous in a simultaneous equation regression. In addition, the method explicitly addresses the bias due to selection effects in credit demand, loan application and approval decisions estimated in the first part. When we disregard selectivity problems and treat collateral and interest rates as exogenous, we find little evidence of the impact of collateral. When we account for these potential biases, collateral is negatively and significantly related to credit rationing. This suggests that conclusions about the impact of collateral on credit rationing drawn from a single-equation regression that ignores selectivity and joint determination of loan terms are likely to be biased. The finding holds whether collateral is measured by a dummy variable (identifying if any type of collateral or guarantee was pledged to secure a loan) or by a continuous variable (reflecting the number of different types of collateral, including guarantees, posited to secure a loan). The result is also robust to alternative estimation methods.

REFERENCES

Almeida, H., Campello, M., Laranjeira, B., and Weisbenner, S. (2012). Corporate debt maturity and the real effects of the 2007 credit crisis. *Critical Finance Review*, 1:3–58.

Amershi, A. H. and Stoeckenius, J. H. W. (1983). The theory of syndicates and linear sharing rules. *Econometrica*, 51(5):1407–1416.

Barnea, A., Haugen, R. A., and Senbet, L. W. (1980). A rationale for debt maturity structure and call provisions in the agency theoretic framework. *Journal of Finance*, 35:1223–1234.

Benjamin, D. (1978). The use of collateral to enforce debt contracts. *Economic Inquiry*, 16:333–359.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S., and Miller, N. H. (2011). Why do borrowers pledge collateral? new empirical evidence on the role of asymmetric information. *Journal of Financial Intermediation*, 20:55–70.

Berger, A. N. and Udell, G. F. (1992). Some evidence on the empirical significance of credit rationing. *Journal of Political Economy*, 100:1047–1077.

Berger, A. N. and Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business*, 68:351–381.

Besanko, D. and Thakor, A. V. (1987). Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets. *In-*

ternational Economic Review, 28:671–689.

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

Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A. (2007). So what do i get? the bank's view of lending relationships. *Journal of Financial Economics*, 85:368–419.

Boot, A. W. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9:7–25.

Boot, A. W. and Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, 35:899–920.

Brander, J. A., Amit, R., and Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, 11(3):423–452.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives*, 33:77–100.

Brunnermeier, M. K. and Yogo, M. (2009). A note on liquidity risk management. *American Economic Review*, 99:578–83.

Campello, M., Giambona, E., Graham, J. R., and Harvey, C. R. (2011). Liquidity management and corporate investment during a financial crisis. *The Review of Financial Studies*, 24:1944–1979.

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

Cerqueiro, G., Ongena, S., and Roszbach, K. (2016). Collateralization, bank loan rates, and monitoring. *Journal of Finance*, 71:1295–1322.

Chakravarty, S. and Yilmazer, T. (2009). A multistage model of loans and the role of relationships. *Financial Management*, 38:781–816.

Chan, Y.-S. and Kanatas, G. (1985). Asymmetric valuation and the role of collateral in loan agreements. *Journal of Money, Credit and Banking*, 17:84–95.

Chan, Y.-S. and Thakor, A. V. (1987). Collateral and competitive equilibria with moral hazard and private information. *Journal of Finance*, 42:345–363.

Chari, V. and Jagannathan, R. (1988). Banking panics, information, and rational expectations equilibrium. *Journal of Finance*, 43(3):749–761.

Chava, S. and Purnanandam, A. (2011). The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics*, 99:116–135.

Cheng, I.-H. and Milbradt, K. (2012). The hazards of debt: Rollover freezes, incentives, and bailouts. *Review of Financial Studies*, 25:1070–1110.

Chui, M., Domanski, D., Kugler, P., and Shek, J. (2010). The collapse of international bank finance during the crisis: evidence from syndicated loan markets. *BIS Quarterly Review*, September:39–49.

Covitz, D. M., Liang, N., and Suarez, G. A. (2013). The evolution of a financial crisis: Collapse of the asset-backed commercial paper market. *Journal of Finance*, 68:815–848.

Dass, N., Nanda, V. K., and Wang, Q. (2011). Syndicated loans: The role of covenants in mitigating lender disagreements. Technical report.

Dennis, S. A. and Mullineaux, D. J. (2000). Syndicated loans. *Journal of Financial Intermediation*, 9:404–426.

Diamond, D. W. (1989). Reputation acquisition in debt markets. *Journal of Political Economy*, 97(4):828–862.

Diamond, D. W. (1991a). Debt maturity structure and liquidity risk. *Quarterly Journal of Economics*, 106:709–737.

Diamond, D. W. (1991b). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, 99(4):689–721.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91:401–19.

Drakos, K. and Giannakopoulos, N. (2011). On the determinants of credit rationing: Firm-level evidence from transition countries. *Journal of International Money and Finance*, 30:1773–1790.

Duchin, R., Ozbas, O., and Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97:418–435.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. *Journal of Finance*, 41:19–37.

Freimer, M. and Gordon, M. J. (1965). Why bankers ration credit. *Quarterly Journal of Economics*, 79:397–416.

Gale, D. and Hellwig, M. (1985). Incentive-compatible debt contracts: The one-period problem. *Review of Economic Studies*, 52(4):647–663.

Gorton, G. and Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, 104:425–451.

Grossman, S. J. and Hart, O. D. (1982). Corporate financial structure and managerial incentives. *The Economics of Information and Uncertainty, edited by John McCall. Chicago: University of Chicago Press*.

Haubrich, J. G. (1989). Financial intermediation: Delegated monitoring and long-term relationships. *Journal of Banking & Finance*, 13(1):9–20.

He, Z. and Milbradt, K. (2016). Dynamic debt maturity. *Review of Financial Studies*, 29:2677–2736.

He, Z. and Xiong, W. (2012a). Rollover risk and credit risk. *Journal of Finance*, 67:391–429.

He, Z. and Xiong, W. (2012b). Dynamic debt runs. *Review of Financial Studies*, 25:1799–1843.

Hess, J. (1985). The use of collateral to enforce debt: Profit maximization. *Economic Inquiry*, 23:349–356.

Hodgman, D. R. (1960). Credit risk and credit rationing. *Quarterly Journal of Economics*, 74:258–278.

Innes, R. D. (1990). Limited liability and incentive contracting with ex-ante choices. *Journal of Economic Theory*, 52:45–67.

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

Ivashina, V. and Scharfstein, D. S. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97:319–338.

Jacklin, C. J. and Bhattacharya, S. (1988). Distinguishing panics and information-based bank runs: Welfare and policy implications. *Journal of Political Economy*, 96(3):568–592.

Jaffee, D. M. and Russell, T. (1976). Imperfect information, uncertainty, and credit rationing. *Quarterly Journal of Economics*, 90:651–666.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3:305–360.

Jiménez, G., Salas, V., and Saurina, J. (2006). Determinants of collateral. *Journal of Financial Economics*, 81:255–282.

Jones, J. D., Lang, W. W., and Nigro, P. J. (2005). Agent bank behavior in bank loan syndications. *Journal of Financial Research*, 28(3):385–402.

Jun, S.-G. and Jen, F. C. (2003). Trade-off model of debt maturity structure. *Review of Quantitative Finance and Accounting*, 20:5–34.

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

Kjenstad, E. C., Su, X., and Zhang, L. (2015). Credit rationing by loan size: A synthesized model. *Quarterly Review of Economics and Finance*, 33:20–27.

Lockett, A. and Wright, M. (2001). The syndication of venture capital investments. *Omega*, 29(5):375–390.

Machauer, A. and Weber, M. (1998). Bank behavior based on internal credit ratings of borrowers. *Journal of Banking and Finance*, 22:1355–1383.

Mian, A. R. and Santos, J. A. C. (2011). Liquidity risk, and maturity management over the credit cycle. *Mimeo, Princeton University*.

Mishkin, F. S. (1992). Anatomy of a financial crisis. *Journal of Evolutionary Economics*, 2(2):115–130.

Mishkin, F. S. (1999). Lessons from the asian crisis. *Journal of International Money and Finance*, 18:709–723.

Morris, S. and Shin, H. S. (2016). Illiquidity component of credit risk—the 2015 lawrence r. klein lecture. *International Economic Review*, 57:1135–1148.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5:147–175.

Ogawa, K. and Suzuki, K. (2000). Demand for bank loans and investment under borrowing constraints: A panel study of japanese firm data. *Journal of the Japanese and International Economies*, 14:1–21.

Panyagometh, K. and Roberts, G. S. (2010). Do lead banks exploit syndicate participants? Evidence from ex post risk. *Financial Management*, 39(1):273–299.

Postlewaite, A. and Vives, X. (1987). Bank runs as an equilibrium phenomenon. *Journal of Political Economy*, 95(3):485–491.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance*, 47(4):1367–1400.

Ross, D. G. (2010). The dominant bank effect: How high lender reputation affects the information content and terms of bank loans. *Review of Financial Studies*, 23(7):2730–2756.

Schmidt, L., Timmermann, A., and Wermers, R. (2016). Runs on money market mutual funds. *American Economic Review*, 106:2625–2657.

Schreft, S. and Villamil, A. P. (1992). Credit rationing by loan size in commercial loan markets. *Economic Review*, (May/June):3–23.

Segura, A. and Suarez, J. (2011). Liquidity shocks, roll-over risk and debt maturity. *CEPR Discussion Paper*, No. DP8324.

Seta, M. D., Morellec, E., and Zucchi, F. (2016). Rollover traps. *Swiss Finance Institute Research Paper No. 16–19*.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance*, 45(4):1069–1087.

Shin, H. S. (2009). Reflections on northern rock: The bank run that heralded the global financial crisis. *Journal of Economic Perspectives*, 23:101–119.

Shleifer, A. and Vishny, R. W. (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives*, 25:29–48.

Simons, K. (1993). Why do banks syndicate loans? *New England Economic Review of the Federal Reserve Bank of Boston*, pages 45–52.

Smith, C. W. J. and Warner, J. B. (1979). On financial contracting: An analysis of bond covenants. *Journal of Financial Economics*, 7(2):117–161.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71(3):393–410.

Stulz, R. and Johnson, H. (1985). An analysis of secured debt. *Journal of Financial Economics*, 14:501–521.

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

Szkup, M. (2013). Optimal debt maturity structure, rollover risk and strategic uncertainty. *mimeo, New York University*.

Watson, H. (1984). Credit markets and borrower effort. *Southern Economic Journal*, 50:802–813.

Williamson, S. D. (1986). Costly monitoring, financial intermediation, and equilibrium credit rationing. *Journal of Monetary Economics*, 18(2):159–179.

Wilson, R. (1968). The theory of syndicates. *Econometrica*, 36(1):119–132.

Xu, Q. (2016). Early refinancing and maturity management in the corporate bond market. *Available at SSRN: https://ssrn.com/abstract=2787968*.

Essay One

2

Refinancing Risk and Debt Maturity Choice During a Financial Crisis

1 INTRODUCTION

The notion that refinancing risk is an important factor to consider in the determination of debt maturity has received much attention in recent years (see, e.g., Brunnermeier, 2009; González, 2015; Paligorova and Santos, 2016).[1] According to this notion, when refinancing risk is present, firms choose longer maturities (Diamond, 1991). The argument is that longer maturities enable firms to avoid concentrating maturity expiration dates (Cheng and Milbradt, 2012; He and Xiong, 012a) and that they allow firms to lengthen their overall debt-maturity structure (He and Milbradt, 2016). These aspects are valued by firms because, in contrast to that of shorter maturities (see, e.g., Jun and Jen, 2003), they lower the rate at which firms seek to refi-

1 Refinancing risk is the risk of being unable to roll maturing debt or that it will have to be refinanced at significantly high interest rates (Froot et al., 1993; Hu, 2010; Valenzuela, 2015).

nance their debt coming due. This aspect can help mitigate exposure to refinancing risk. While theoretical work relates refinancing risk to debt-maturity choice and firms have expressed concerns about refinancing risk during the recent financial crisis, much less is known about the empirical link.

This study's research objective is to empirically explore refinancing-risk considerations as an important determinant of debt-maturity choice by examining the relationship between firms' potential for exposure to refinancing risk and the maturity of new loans obtained during the 2007–2009 financial crisis. Since this crisis resulted in a secular decline in credit supply (see, e.g., Ivashina and Scharfstein, 2010), it provides a useful empirical laboratory for studying such relationships. This study thus helps to understand how well the theory squares with how firms have responded to the financial crisis—do firms with refinancing risk display debt-maturity choice behavior consistent with the theoretical prediction? The answer is far from obvious.

There is a compelling economic reason to expect firms for whom refinancing risk is a real concern to actively engage in lengthening their debt maturity to alleviate exposure to refinancing risk. These firms would stand to absorb an economically significant cost if they are unable to roll over their maturing debt. This includes an inefficient liquidation by creditors (Diamond, 1991; He and Xiong, 012a), the sale of assets at fire-sale prices (Brunnermeier and Yogo, 2009; Shleifer and Vishny, 2011; Choi et al., 2013) and missed profitable investments (Duchin et al., 2010; Almeida et al., 2012). Considering such significant costs, one would expect firms with refinancing risk concerns to exhibit maturity-choice behavior in line with the theory's prediction.

On the other hand, while the theoretical basis for expecting a maturity effect from refinancing-risk considerations is strong, it is less clear if firms with refinancing risk are able to raise debt with longer maturities in a tight credit market. Creditors may adopt more restrictive lending policies during these times. In fact, studies examining the effects of the recent financial crisis document several pieces of evidence consistent with this argument. For example, Chui et al.

(2010) and Ivashina and Scharfstein (2010) find that the financial crisis led to a contraction in the supply of bank loans. Kwan (2010), Campello et al. (2011) and Puri et al. (2011) note that financial institutions tightened their lending standards. González (2015) and Paligorova and Santos (2016) document further evidence that creditors shortened the maturity of loans to reduce the maturity mismatch on their balance sheets—i.e., the mismatch between the maturity of the loanable funds they raise and the loans they offer. Given these manifestations of the financial crisis, some firms obviously find it difficult to raise funds. This makes the research question pursued in this paper particularly interesting, precisely because theory suggests a systematic pattern of maturity management behavior that reflects the refinancing-risk concern to be displayed in those times when obtaining financing is challenging.

Establishing a causal relationship between firms' potential for exposure to refinancing risk and the maturity of new loans issued is, however, challenging. A major challenge confronting the empirical attempt relates to the applied measure of refinancing risk. While the corporate finance literature widely blames excessive reliance on shorter maturities for firms' exposure to refinancing risk (see, e.g., Brunnermeier, 2009), empirical frameworks in which short-term debt on the balance sheets is used to measure a firm's exposure to refinancing risk suffer from endogeneity bias. That is, since maturity choice is an endogenous decision, the preference for outstanding short-term debt might also be influenced by the same factors that affect the maturity of a newly issued debt. To overcome this problem, the recently emerging literature on refinancing risk has used long-term debt coming due in one year to identify the variation in firms' exposure to refinancing risk (see, e.g., Hu, 2010; Almeida et al., 2012; Harford et al., 2014; Gopalan et al., 2014). Yet, even using this measure as an identification tool in this article is likely to raise some concerns.

One potential concern stems from classifying a wide spectrum of financial obligations coming due in one or more years as long-term debt. This classification indicates that it is not unlikely for long-term debt maturing within a year to be partly explained by the firm's current risk characteristics, suggesting that measures of this type are endogenous. An issue of another concern is that, since the financial crisis spans over the period 2007–2009, for instance, long-term debt outstanding in 2007 and that comes due in 2008 is obviously affected by the crisis. This long-term debt becomes endogenous with regard to its impact on the maturity of new loans issued in 2008. Also, it is not unlikely for firms to anticipate and prepare for the crisis by refinancing a portion of long-term debt expected to come due during the crisis. In fact, there is evidence supporting this argument (see, e.g., Mian and Santos, 2011; Xu, 2016). These concerns suggest that statistical tests are likely to be confounded; thus, it is difficult to make causal claims with empirical tests in which long-term debt maturing in one year is used as an identification tool.

The current study addresses the above-mentioned concerns by predetermining firms' exposure to refinancing risk during the 2007–2009 financial crisis. More precisely, the relationship between refinancing risk and the maturity of new loans is tested by exploiting the maturity profile of long-term debt many years back before the scheduled due date during the financial crisis to identify the variation in firms' potential for exposure to refinancing risk. Since this variable is unlikely to be affected by the firm's behavior during the crisis, it can serve as an exogenous measure and help to isolate the causal effect of refinancing risk on the maturity of loans issued during the crisis period. The estimation is based on loan-level data for U.S. firms from the DealScan database.

The analysis provides evidence that firms with refinancing risk choose longer maturities during the financial crisis. The maturity effect of refinancing risk is statistically significant and economically nonnegligible. As the estimated coefficients suggest, a one-standard-deviation increase in the maturing portion of outstanding long-term debt out of total long-term debt measured at the end of year 2004 leads to about a 3.5% increase in the maturity of new loans relative to the sample mean. This positive empirical relationship is consistent with the theoretical prediction that firms with different exposures to refinancing risk choose their maturities differently. In particular, this relationship can be interpreted as firms choosing longer maturities to mitigate their exposure to refinancing risk. Such a relationship is unlikely to be explained by the alternative interpretation that the observed association is part of a general pattern whereby firms replace maturing long-term debt with new loans of longer maturity. The estimated precrisis negative relationship does not support this alternative hypothesis.

Building on this baseline result, this study next examines whether the maturity effect of refinancing risk varies between different groups of firms. If alleviating refinancing risk exposure is the force driving the observed relationship, one would expect the effect to be stronger for firms that are more concerned about refinancing risk. In line with this expectation, the analysis provides evidence that the effect is more pronounced for firms with speculative-grade ratings than unrated and investment-grade firms. This result can be understood in light of the evidence that firms with limited access to public debt markets are the most affected by the recent crisis (see, e.g., Campello et al., 2010). Hence, they are expected to display strong refinancing-risk concerns. While both unrated and speculative-grade firms are widely believed to have restricted access to public debt finance, a potential explanation for the differential impact between them may be that financial institutions restrict unrated firms from participating at the very long end of the maturity spectrum.

The analysis provides further evidence that the effect also varies between firms classified according to internally generated liquidity. More precisely, the effect is stronger for firms with low cash flows. Such differential impact can be understood in light of the theoretical suggestion (see, e.g., Chen et al., 2012) and empirical evidence (see, e.g., Choi et al., 2013) that firms with low cash flows favor longer debt maturity because their debt is more risky, and they will face greater refinancing risk. In keeping with the recent relationship literature's argument that establishing lending relationships with creditors is particularly valuable in times of crisis (see, e.g., Hainz and Wiegand, 2013; Gobbi and Sette, 2014; Bolton et al., 2016), the analysis shows that firms with refinancing risk obtain longer maturities from their established relationship lenders.

The baseline result is strongly robust to alternative estimation techniques and model specifications. For example, the matching method shows that, except for the maturing long-term debt, otherwise similar firms that need to roll over a large amount of debt issue new loans that are of longer maturity. This result can alleviate a potential concern related to sample-selection bias that may arise from the possibility that firms obtaining credit during the financial crisis may be a nonrandom sample. One might suspect that firms that normally issue shorter maturities may be excluded from the loan market. If so, such selection may put an upward pressure on the refinancing-risk effect. The main result also remains statistically significant in the alternative specifications that control for bank fixed effects and clustering the standard errors at the bank level.

This study contributes to the empirical literature on determinants of corporate debt maturity choice. Existing research has made significant progress in explaining the determinants of debt maturity. For example, some studies (see, e.g., Barclay and Smith, 1995; Guedes and Opler, 1996; Johnson, 2003; Billett et al., 2007) show that firms who want to reduce agency costs of debt, such as asset substitution and underinvestment, choose shorter maturities. Others (see, e.g., Mitchell, 1993; Barclay and Smith, 1995; Berger et al., 2005) show that firms with a higher level of information asymmetry choose shorter maturities. Others argue that firms time the credit markets to determine the maturity that reduces the financing costs (see, e.g., Butler et al., 2006). The current article extends this line of research by identifying refinancing risk as an important factor influencing corporate debt-maturity choices during uncertain funding conditions.

In providing a new perspective on the maturity effects of refinancing risk, this paper is closely related to the recent empirical studies by Mian and Santos (2011) and Xu (2016). These studies focus on early refinancing—i.e., refinancing before loans reach their maturity date. The evidence they provide suggests that firms manage the maturity of their debt by issuing longer maturities during good credit times to minimize their exposure to liquidity risk during tight credit conditions. The current article distinguishes itself from these studies in two ways. First, this analysis focuses on refinancing risk associated with the roll over of maturing debt. Second, the analysis examines maturity decisions during bad credit market conditions. In doing so, this study adds to the above literature by showing that firms with refinancing risk display maturity-lengthening behavior even during crisis times.

The remaining sections of this article are structured as follows. Section 2 briefly reviews the theoretical underpinnings behind the refinancing risk in credit markets. Developing an empirically testable refinancing-risk–maturity prediction is also the topic of this section. Section 3 describes the data used for the analysis and constructs the refinancing-risk measures. The empirical results demonstrating the effects of refinancing risk on loan-maturity decisions are presented in Section 4. While Sections 5 and 6 present the analysis that investigates whether the effect of refinancing risk varies across different firms and loans, Section 7 undertakes additional robustness checks. The article closes with a conclusion in Section 8.

2 THEORY AND TESTABLE HYPOTHESES

The idea that refinancing-risk considerations can influence corporate debt-maturity choice was originally presented by Diamond (1991). Yet, this topic has not until recently occupied a central position in the corporate debt-maturity-choice literature. The increased attention this notion has received in recent years was inspired by the 2007–2009 financial crisis. Following this crisis, a growing number of finance studies have investigated not only the extent to which the choice of shorter versus longer maturities can expose firms to refinancing risk (see, e.g., Brunnermeier, 2009; He and Xiong, 012a,b; Morris and Shin, 2016; Seta et al., 2016), but also to what extent firms choose shorter versus longer maturities in anticipation of refinancing risk (see, e.g., Cheng and Milbradt, 2012; Szkup, 2013; He and Milbradt, 2016). They argue that firms may be unable to roll over shorter-maturing debt at times when refinancing coincides with tight credit-market conditions or weaker firm fundamentals.

A large body of recent literature provides the mechanism that links tight credit-market conditions and refinancing risk. For example, studies by Brunnermeier (2009), Gorton (2009), Acharya et al. (2011), Gorton and Metrick (2012), Covitz et al. (2013), Schroth et al. (2014) and Schmidt et al. (2016) suggest that the 2007–2009 financial crisis generated refinancing risk for firms through its impact on money markets such as the commercial paper markets, overnight sale and repurchase (repo) markets, and interbank lending markets. They document different episodes that show the freeze in money markets, which led to the wholesale funding liquidity dry-up as investors shied away to avoid losses. The liquidity dry-up in these funding markets made it difficult for the financial institutions to raise loanable funds and, thereby, translated into considerable credit-supply shrinkage (see, e.g., Ivashina and Scharfstein, 2010). The disruption of the supply of credit generally led to an increase in firms' refinancing risk.

Another theoretical literature offers a different mechanism that connects weaker firm fundamentals and refinancing risk. For example, Cheng and Milbradt (2012), He and Xiong (012a,b), and Morris and Shin (2016) note that deterioration in a firm's future fundamentals creates interdependence among the creditors of the firm in terms of their willingness to refinance. Using debt-rollover models, they show that the current creditors, who face uncertainty about future creditors' rollover decisions, refuse to roll over the currently maturing debt to avoid absorbing costs in the event of liquidation by future creditors. In the presence of the well-established coordination problems among multiple creditors, uncertainty about future valuation of the underlying asset could undermine current creditors' confidence. Thus, they may not allow refinancing to take place.

Irrespective of the sources of refinancing risk discussed above, firms are exposed to refinancing risk through the maturity structure of their debt. The corporate finance literature has long recognized the importance of adjusting debt's maturity structure in the presence of uncertain financing conditions. For example, Diamond (1991, p. 718) vividly states that "if liquidity risk is absent, then short-term debt is preferred. If liquidity risk is present, then long-term debt can be preferred".[2] Longer maturities can help hedge against refinancing risk mainly because they permit firms to spread out the expiration period across an extended time (Cheng and Milbradt, 2012; He and Xiong, 012a). This means that, with longer maturities, refinancing needs increase at a much slower rate, reducing the frequency with which the firm needs to tap the credit markets.

One may argue that firms can still issue shorter maturities and continually roll them over, as in the spirit of the model by Leland (1998) and He and Xiong (012a). While such debt-maturity policies could be adopted by some firms, those with refinancing risk may not afford the strategy of repeatedly rolling over maturing short-term debt without exacerbating their refinancing risk. The reason is that shorter maturities increase the speed at which firms need the next refinance (Jun and Jen, 2003); that high rollover frequency ultimately diminishes collateral value and debt capacity (Acharya et al., 2011). Due to the feedback effect, adding additional shorter maturities ultimately exposes firms with refinancing risk to tight credit-market conditions—i.e., unable to refinance or forced roll over debt at prohibitively high interest rates.

While longer maturities can help to alleviate exposure to refinancing risk, it is important to note that they may also introduce agency and incentive-related problems. A well-established literature argues that shorter maturities can alleviate maturity-induced conflicts such as asset substitution (Jensen and Meckling, 1976; Barnea et al., 1980) and debt overhang (Myers, 1977), align shareholder–manager interests (Grossman and Hart, 1982), reduce costs of capital (Taggart, 1977; Jun and Jen, 2003), and decrease the misvaluation of debt due to information asymmetry (Flannery, 1986). This shows that, when determining debt's maturity, firms generally face a trade-off between minimizing refinancing risk and maintaining low agency and incentive-related friction. Hence, firms' maturity choices depend on which problem dominates. With drastic credit-supply shrinkage and increased lending standards during the recent financial crisis, if refinancing risk concerns outweigh those of agency-related frictions,

2 In the above-cited article, liquidity risk is defined similarly to refinancing risk.

firms with refinancing risk are expected to choose longer maturities. This empirical prediction is expressed in Hypothesis 1.

Hypothesis 1 (Refinancing-Risk–Maturity Hypothesis)**:** *Firms with refinancing risk choose longer maturing loans during the 2007–2009 financial crisis.*

Many extensions of the refinancing-risk–maturity prediction are also examined. For example, whether refinancing risk's maturity effect varies between firms classified on the basis of their position in accessing external debt financing. The extensive empirical literature assessing the effects of the 2007–2009 financial crisis has documented that firms with limited access to public debt markets are most exposed to negative credit-supply shocks (see, e.g., Chava and Purnanandam, 2011; Hale and Santos, 2013; Chiu et al., 2014). There is also evidence that these firms experienced credit rationing in capital markets (see, e.g., Campello et al., 2010). Consequently, one may expect firms' maturity choices to respond differently to refinancing-risk concerns depending on the their relative access to external debt financing.

Another strand of recent literature emphasizes the importance of internal financial constraints for firms' exposure to refinancing risk. For example, Chen et al. (2012) build a dynamic debt-maturity–choice model in which firms generating low cash flows favor longer debt maturities because they would otherwise incur higher rollover costs. A theoretical perspective behind this argument is that low cash flows (i.e., weaker firm fundamentals) tend to drive down the market value of debt, mainly because the debt becomes riskier. When this happens, as noted by Seta et al. (2016), firms incur refinancing losses from issuing new debt to replace maturing debt. He and Xiong (012a) demonstrate that an increase in rollover losses endogenously drives up firm defaults. An increase in defaults, as He and Xiong (012b) shows by deriving a rollover threshold equilibrium, exacerbates debt runs. That is, it encourages creditors not to roll over their debt contracts with the firm to avoid absorbing costs in the event of a liquidation. One may, thus, expect refinancing-risk concerns to encourage firms with limited internally generated funds to lengthen their debt maturity.

Several recent studies in the relationship literature show a connection between building lending relationships with creditors and being exposed to credit-supply disruptions. For example, the Bolton et al. (2016) model predicts that firms that borrow from relationship-based lending are better able to limit the impact of shocks during crisis times. They find evidence that firms secure better continuation financing from their relationship lenders. Gobbi and Sette (2014) also offer evidence that firms who concentrate borrowing from fewer banks manage to reduce a contraction in the availability of bank credit while those borrowing from more banks suffer a larger contraction. Further evidence is provided by Hainz and Wiegand (2013), who show that relationship lending helps firms avoid a deterioration in nonprice contract terms, such as collateral and maturity. According to these studies, firms with refinancing risk can obtain longer maturities from their relationship lenders.

3 THE DATA SET

3.1 *Data Source and Sample Construction*

To conduct empirical tests of Hypothesis 1, this paper uses data from two sources. Loan-specific information is extracted from Thomson-Reuters LPC's DealScan database. This data source provides detailed information on loan facilities made to U.S. firms by U.S. and foreign financial intermediaries. Loan facilities reported by the DealScan database are syndicated and unsyndicated loans. This article uses both types to investigate how refinancing-risk considerations may influence maturity choices at the time of loan origination. To this end, information on the maturity and amount of the loan, facility start date and loan type and purpose is collected for all loan facilities.

Quarterly information from the firms' balance sheet is extracted from the Compustat database because DealScan does not provide sufficient information on firm-specific characteristics, though it does report the firm's identity. The two data sources, however, do not have a common identifying code between them. This study, thus, uses the *DealScan–Compustat* link table constructed by Michael Roberts and Wharton Research Data Services to merge the loan-facility information to the borrowing firm's financial information.[3] This link table combines the corresponding information in the two data sources on the basis of the borrowing company name. Loan facilities that cannot be merged to the corresponding firm's financial information using this link table are excluded from the analysis.

The analysis is based on the sample drawn from the DealScan–Compustat merged database. The sample construction begins by focusing on U.S. firms as borrowers. In keeping with previous empirical studies, the sample is restricted to nonfinancial borrowers by excluding firms in the financial sectors (those with primary Standard Industrial Classification (SIC) codes between 6000 and 6999). Firm–year observations with negative values for total assets are also removed from the sample.

This paper measures a firm's potential for exposure to refinancing risk using the maturing portion of outstanding long-term debt, discussed in detail in a subsequent subsection. It is therefore crucial to clean inconsistencies in the long-term-debt entries. For this purpose, the following filtering strategies are applied as in Hu (2010), Almeida et al. (2012) and Li (2013). Firm–year observations with negative values of long-term debt maturing in one, two, three, four or five years are removed from the sample. Also, firm–year observations for which long-term debt maturing in one, two, three, four or five year is greater than total long-term debt are dropped from the sample.

The sample is further restricted to facilities originated between August 2007 and June 2009 because the paper investigates the relationship between refinancing risk and loan maturity during the recent financial crisis. The origin of this crisis goes back to the collapse of the U.S. subprime loan market during the summer of 2007. Accordingly,

3 For a detailed description of how the DealScan–Compustat link table was constructed, refer to Chava and Roberts (2008).

studies widely attribute August 2007 as the beginning period of the financial crisis (see, e.g., Duchin et al., 2010; Ivashina and Scharfstein, 2010). This study considers June 2009 as the end of the sample period because the National Bureau of Economic Research notes that the financial crisis ended at the end of the second quarter of 2009.

3.2 *Measuring Dependent and Control Variables*

Since the aim of this article is to examine how refinancing-risk considerations may affect debt-maturity decisions, the maturity (*Maturity*) of new loans obtained during the recent financial crisis is used as the dependent variable. The maturity of incremental debt issues is more relevant for the purpose of this study than the maturity of all financial obligations on the firm's balance sheet. DealScan measures the maturity of loans by the number of months from the loan start date to the end date.

In keeping with the prediction of the broad categories of the theoretical literature and prior empirical studies of the debt-maturity decision, a large number of loan-level and firm-specific characteristics are used as control variables. Loan size (*Loan Size*) is measured by the natural logarithm of loan facility amount in U.S. dollars. This paper constructs four dummies to indicate whether the type of the loan facility is a revolver (*Revolver*), term loan (*Term Loan*), 360-day facility (*364-Day Facility*) or another loan type (*Other Type*). Five indicator variables are also constructed to identify whether the purpose of the loan facility is for a corporate purpose (*Corporate Purpose*), working capital (*Working Capital*), debt repayment (*Debt Repay*), takeover (*Takeover*) or another loan purpose (*Other Purpose*) .

Firm size (*Firm Size*) is measured by the natural logarithm of the book value of total assets. Earnings before interest, taxes, depreciation and amortization scaled by total assets is used to measure firm profitability (*Profitability*). Market-to-Book (*Market-to-Book*) is measured as the ratio of the book value of total assets minus the book value of equity plus the market value of equity to total assets. Firm leverage (*Leverage*) is measured by the ratio of total debt (i.e., the sum of debt in current liability and long-term debt) to total assets. The firm's tax payment (*Taxes*) is measured by the ratio of total tax payment scaled by total assets. Cash flow (*Cash Flow*) is measured by operating income before depreciation (Compustat item OIBDPQ) over total assets.

Following Gopalan et al. (2014), an ordinal credit rating variable (*Rating*) is constructed based on a firm's Standard & Poor's (S&P) long-term domestic-issuer credit rating as a measure of its credit quality. Following Benmelech et al. (2015), asset maturity (*Asset Maturity*) is measured by net property, plant, and equipment divided by depreciation expenses. Following Bharath et al. (2007, 2011), relationship lending (*Relationship*) is measured by the ratio of the number of previous interactions between the firm and the lender of a loan in the last five years, scaled by the total number of loans the firm has borrowed over the same time period. All variables used in this study are formally defined in the appendix.

3.3 *Measuring Refinancing Risk Exposure*

To construct a measure of a firm's exposure to refinancing risk, this study uses information on long-term debt payable in the first (Compustat item dd1), second (Compustat item dd2), third (Compustat item dd3), fourth (Compustat item dd4) and fifth (Compustat item dd5) year, as provided by the Compustat database. Accordingly, the refinancing risk exposure ratio is computed as

$$Maturing/LT_{f,t} = \frac{dd_{2004,f,t}}{(dd1 + dltt)_{2004,f}}, \qquad (1)$$

where $Maturing/LT_{f,t}$ is defined as the proportion of the amount of firm f's long-term debt outstanding at year-end 2004 with the repayment due date in year t ($dd_{2004,f,t}$) out of the firm's total long-term debt outstanding at year-end 2004 ($(dd1 + dltt)_{2004,f}$). As an alternative measure, the proportion of long-term debt outstanding at the end of year 2004 and that comes due in year t scaled by total assets at the end of year 2004 ($Maturing/AT_{f,t}$) is also constructed.

A higher value of $Maturing/LT_{f,t}$ and $Maturing/AT_{f,t}$ means that a large amount of long-term debt is coming due in year t. Evidently, a higher level of maturing debt increases firms' refinancing risk, because firms with a higher volumes of debt maturing soon are more likely to repeatedly tap credit markets. Hence, these variables can serve as a proxy measure of firms' potential for exposure to refinancing risk. Since they are constructed in such a way that they predetermine firms' exposure to refinancing risk, these measures alleviate concerns associated with the use of short-term debt and long-term debt maturing in one year discussed in the introduction.

3.4 *Descriptive Statistics*

The summary statistics of the DealScan–Compustat dataset on which the debt-maturity effect of refinancing risk are analyzed is presented in Table 1. Panel A of this table reports summary statistics of the maturing portion of outstanding long-term debt constructed based on the data in year 2004. These summary statistics are calculated at the firm–year level, as some borrowers appear in the sample more than once. Panel B displays the descriptive statistics of new loans, which are calculated at a loan-facility level. Summary statistics of the borrowing firms' financial information, which are calculated at the firm–quarter level, are presented in Panel C.

With regard to the maturing portion of long-term debt outstanding, the results depicted in Panel A show considerable variation among firms. For instance, the values that the variable *Maturing/LT* takes vary between 0.00 and 1.00, with the mean of 0.11. The distribution of this variable indicates that, on average, 11% of long-term debt outstanding as of the year-end 2004 matures during the financial crisis. The maximum value of this variable indicates that some firms have 100% of their outstanding long-term debt coming due at some point during the recent financial crisis. On the other hand, the minimum value indicates that some firms have none of their long-term debt coming due during the crisis. Given this wide cross-firm variation in the amount of long-term debt scheduled to mature during the recent

Table 1. Summary Statistics

This table presents summary statistics of the data. Panel A reports summary statistics of the maturing portion of outstanding long-term debt constructed based year-2004 data. These summary statistics are calculated at the firm–year level. Panel B presents summary statistics of new loans, which are calculated at a loan-facility level. Panel C displays statistics on the borrowing firms' financial information, which are calculated at the firm–quarter level. Summary statistics of cash flows scaled by total assets measured in 2006 (average of quarter 1 to quarter 4) are calculated firm level. Summary statistics of S&P credit ratings measured, as of the end of June 30, 2007, are also calculated at the firm level. All variables are defined in the appendix.

				Distribution				
	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max
Panel A: Maturing Long-Term Debt								
Maturing/LT	1,068	0.11	0.19	0.00	0.00	0.04	0.14	1.00
Maturing/AT	1,068	0.04	0.08	0.00	0.00	0.01	0.03	0.76
Panel B: Loan Characteristics								
Maturity	1,629	45.21	26.26	1.00	24.00	48.00	60.00	300.00
Amount (million)	1,687	590.82	1,476.00	0.00	60.30	200.00	500.00	22,500.00
Term Loan	1,687	0.29	0.45	0.00	0.00	0.00	1.00	1.00
Revolver	1,687	0.53	0.50	0.00	0.00	1.00	1.00	1.00
364-Day Facility	1,687	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Corporate Purpose	1,687	0.40	0.49	0.00	0.00	0.00	1.00	1.00
Working Capital	1,687	0.20	0.40	0.00	0.00	0.00	0.00	1.00
Takeover	1,687	0.12	0.32	0.00	0.00	0.00	0.00	1.00
Debt Repay	1,687	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Relationship	1,549	0.63	0.48	0.00	0.00	1.00	1.00	1.00
Panel C: Borrower Characteristics								
Total AssetB	1,070	10.75	41.70	0.01	0.56	1.88	6.43	797.77
Market-to-Book	975	1.52	0.79	0.31	1.00	1.31	1.76	4.70
Profitability	1,044	0.03	0.03	−0.21	0.02	0.03	0.05	0.16
Leverage	1,048	0.30	0.21	0.00	0.15	0.28	0.40	1.03
Taxes	1,068	0.00	0.01	−0.11	0.00	0.00	0.01	0.14
Utility Industry	1,143	0.15	0.36	0.00	0.00	0.00	0.00	1.00
Asset Maturity	1,038	34.40	27.32	0.42	15.01	25.11	44.42	128.13
Cash Flow	798	0.03	0.03	−0.22	0.02	0.03	0.05	0.17
No Rating	887	0.46	0.50	0.00	0.00	0.00	1.00	1.00
SG Rating	887	0.27	0.44	0.00	0.00	0.00	1.00	1.00
IG Rating	887	0.27	0.44	0.00	0.00	0.00	1.00	1.00

financial crisis, it is not unreasonable to expect significant differences in the firms' exposure to refinancing risk. This difference would provide a natural motivation to investigate whether these variations also translate into a significant variation in loan-maturity choices.

In terms of loan characteristics, loan facilities have an average maturity of 45 months and the median maturity of 48 months, with maturity ranges from 1 to 300 months. The facility amount is US$ 590.8 million on average and varies between US$ 549,700 and US$ 22.5 billion. Most loan facilities (53% of the loans in the sample) are in the form of a revolver. The next largest loan type is a term loan, which accounts for 29% of the facilities in the sample. Firms issue a significant fraction of loan facilities for corporate purposes, 40% of the loans in the sample. The other main purposes for which firms issue loan facilities are working capital (20%) and takeover (12%). Most loan facilities (63%) are obtained from relationship lenders.

With respect to firm characteristics, a borrower has US$ 10.75 billion total assets on average each quarter, varying between US$ 12 million and US$ 797.77 billion. The average firm has 3% profitability per quarter. Firm leverage and asset maturity are Winsorized at the 99^{th} percentile to eliminate extreme outliers from influencing the results. After Winsorization, the average firm is leveraged at 30% each quarter, and the average asset maturity is 34.4 months. The mean cash-flow-to-asset ratio measured in year 2006 (average of quarter 1 to quarter 1) is 0.12. In terms of long-term issuers' credit ratings measured at the end of June 30, 2007, 46% of the firms in the sample have no S&P credit ratings while 27% have a speculative-grade credit rating.

4 REFINANCING RISK AND LOAN MATURITY: EMPIRICAL EVIDENCE

4.1 *Model Specification*

To investigate the impact of refinancing risk on loan-maturity choice, this article estimates a loan-maturity regression model of the form

$$Maturity_{l,f,t} = \alpha + \beta Refinancing\ Risk_{f,t} + \gamma X_{f,t-1} + \eta X_{l,t} + FE_{\text{industry}} + FE_{\text{time}} + \epsilon_{l,f,t}, \quad (2)$$

where $Maturity_{l,f,t}$ denotes the term to maturity of loan facility l obtained by firm f at time t. From the point of view of Hypothesis 1 developed in Section 2, the key independent variable of interest is $Refinancing\ Risk_{f,t}$. The proportion of long-term debt that comes due during the 2007–2009 financial crisis, measured based on data as of the year-end 2004, is used to proxy for this variable. According to the refinancing-risk–maturity prediction, firms with refinancing risk should display a strong tendency to issue longer maturities. Thus, the main coefficient of interest, β, should be positive. This model also controls for firm-specific ($X_{f,t-1}$) and loan-level ($X_{l,t}$) characteristics, which are presented as firm and loan controls for clarity.

Firm Controls. Agency-based theories of debt-maturity choice argue that short-term debt alleviates the problems of underinvestment (Myers, 1977) and asset-substitution (Barnea et al., 1980). Since small firms are more likely to face greater agency problems (Smith and Warner, 1979), they are expected to have more short-term debt. Thus, *Firm Size* is used as a control variable. Firms with growth opportunities are also more likely to face greater agency conflicts between shareholders and debt holders. For investment opportunities that involve growth options, Myers (1977) argues that choosing debt that matures before growth options are exercised mitigates underinvestment problems. Since firms with higher market-to-book ratios are expected to have greater growth options, they are expected to use short-term debt. Hence, this paper controls for growth options using *Market-to-Book*.

Theoretical work by Morris (1992) and Leland and Toft (1996) shows that firms who choose greater leverage also prefer to choose longer maturity. Since higher leverage involves greater bankruptcy risk, issuing long-term debt allows firms to minimize exposure to such risk. According to these studies, there is a positive relationship between leverage and debt maturity. However, Dennis et al. (2000) argue that higher leverage increases agency costs by encouraging managerial opportunism. They argue that creditors use short-term debt for firms with higher leverage to discourage such opportunism, suggesting a negative relationship. Accordingly, this paper controls for such possibilities using *Leverage*.

Brick and Ravid (1985) and Kane et al. (1985) develop theoretical models of optimal debt-maturity structures that incorporate taxes. They argue that managers can increase firm value by choosing long-term debt when the tax advantage of debt decreases. Thus, this paper controls for this possibility using *Taxes*. Flannery (1986) argues that short-term debt allows firms suffering from informational problems to mitigate the mispricing of debt associated with information asymmetries. Shorter maturities reduce the misvaluation of debt by allowing costs of financing to depend on the arrival of favorable information. Diamond (1991) argues that low- and high-quality firms issue short-term debt, while medium-quality firms use long-term debt. This paper controls for information asymmetries and credit qualities using *Rating*.

Barclay and Smith (1995) argue that utility industries suffer less from agency-related problems because authorities regulate them. A reduction in the agency problem may thus allow firms in the utility industry to borrow longer-maturing debt. This paper thus controls for regulated industries using the dummy variable *Utility Industry*. Following Xu (2016), this paper also controls for firm profitability (*Profitability*).

According to the matching principle, firms should match the maturity of the debt they issue with the maturity of their assets. The reason is that if debt matures before assets produce cash, firms many not be able to honor their debt-repayment schedule. Further, Myers (1977) argues that matching the maturity of debt with the maturity of assets mitigates agency conflicts. The matching principle thus suggests that longer asset maturity supports long-term debt. This paper controls for this notion using *Asset Maturity*. Goswami (2000) argues that information asymmetries regarding firms' cash flow may induce a nonlinear relationship between the maturity of debt and asset maturity. This study controls for such a possibility using the square of asset maturity (*Asset Maturity*^{2}).

Loan Controls. The maturity model controls for loan amounts using *Loan Size*. In all model specifications, *Revolver*, *Term Loan* and *364-Day Facility* dummies are used to control for the loan type. Additionally, *Corporate Purpose*, *Working Capital*, *Debt Repay* and *Takeover* dummies are used to control for loan purpose.

Fixed-effect dummies and clustering. Since debt-maturity policies can differ between industries, the model controls for industry-level fixed effects with industry dummies using a one-digit SIC code (*Industry Dummy*). Further, debt-maturity choices can also vary with time. The regression model accounts for this possibility by allowing for year-specific effects with time dummies (*Time Dummy*). Because there are few observations for each firm, this paper cannot include firm-level fixed-effect dummies in the model. Standard errors are clustered at a firm level and allowed to be heteroskedastically robust.

4.2 *Loan Maturity Regression Analysis: Testing Hypothesis 1*

If maturity lengthening can help firms reduce their exposure to refinancing risk, one would expect to observe firms with refinancing risk actively involved in lengthening their debt's maturity structure. Such maturity-management practices are expected more among firms with a large amount of debt coming due soon, because a large volume of maturing debt would put firms at greater refinancing risk in times of financial crisis. This positive relationship is the prediction of Hypothesis 1 developed in Section 2, and is tested using the maturity regression model given in Equation (2). Table 2 reports baseline results from the empirical analysis of how the maturing portion of outstanding long-term debt is related to the maturity of loans obtained during the 2007–2009 financing crisis.

The results show that firms with a large portion of their debt maturing during the crisis experience an increase in the maturity of newly issued loans. As can be seen from the results presented in Column (1), the regression coefficient for the relationship between the

Table 2. Loan-Maturity Regression Analysis: Testing Hypothesis 1

This table presents coefficient estimates from regressions relating the maturing portion of outstanding debt to the maturity of new loans obtained during the 2007–2009 financial crisis. The dependent variable, *Maturity*, is the maturity of loans. Columns (1) and (2) report the estimated coefficients for the sample period from August 2007 to June 2009. Columns (3) and (4) display the coefficient estimates for the sample period from August 2007 to December 2008. The independent variables of interest, *Maturing/LT* and *Maturing/AT*, are the proportion of maturing outstanding long-term debt scaled by total long-term debt and total assets, respectively. Definitions of the remaining variables are provided in the appendix. In all columns, standard errors are clustered at the firm level and are heteroskedastically robust. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity			
	As of year-end 2004 August 2007–June 2009		As of year-end 2003 August 2007–December 2008	
	(1)	(2)	(3)	(4)
Maturing/LT	8.339^{**}		7.633^{*}	
	(3.28)		(4.10)	
Maturing/AT		36.077^{***}		28.200^{**}
		(11.33)		(12.49)
Loan Size	2.771^{***}	2.685^{***}	2.818^{***}	2.793^{***}
	(0.73)	(0.72)	(0.91)	(0.90)
Firm Size	-1.792^{**}	-1.720^{*}	-1.632	-1.586
	(0.88)	(0.88)	(1.02)	(1.02)
Market-to-Book	-1.699^{**}	-1.676^{**}	-1.433	-1.377
	(0.85)	(0.85)	(1.02)	(1.01)
Profitability	83.159^{***}	79.881^{***}	122.871^{***}	118.941^{***}
	(28.63)	(28.50)	(43.72)	(43.72)
Leverage	-1.628	-3.962	-3.005	-4.164
	(5.20)	(5.20)	(5.12)	(5.11)
Taxes	-54.726	-53.695	-128.732^{*}	-125.354^{*}
	(50.43)	(49.34)	(71.94)	(70.84)
Rating	0.044	0.051	0.116	0.133
	(0.18)	(0.18)	(0.21)	(0.21)
Utility Industry	-11.644	-11.942	-6.651	-6.317
	(8.43)	(8.41)	(5.52)	(5.55)
Asset Maturity	0.046	0.027	0.019	0.035
	(0.12)	(0.12)	(0.13)	(0.13)
$[Asset\ Maturity]^2$	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Loan Type Dummy	YES	YES	YES	YES
Loan Purpose Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES
Time Dummy	YES	YES	YES	YES
R^2	0.332	0.336	0.314	0.316
N	1,272	1,272	954	954

maturing portion of outstanding long-term debt and the maturity of new loans is positive and significant at the 5% level. In addition to being statistically distinct from zero, this baseline result is also economically nonnegligible. The estimated coefficient on *Maturing/LT* suggests that a one-standard-deviation increase in the maturing portion of outstanding long-term debt is associated with an increase of around two months in the maturity of newly obtained loans. Given that the average loan maturity is 45.21 months, this increase corresponds to about 3.5% relative to the sample mean. This baseline result is robust to a different measure of refinancing risk. As can be noted from the coefficients reported in Column (2), *Maturing/AT* has a positive and highly significantly (at the 1% level) estimated coefficient.

This baseline result can be viewed as providing empirical support to the notion that refinancing-risk considerations matter for corporate debt-maturity choices in crisis times. As such, firms with refinancing risk design a maturity-choice strategy by considering the implication of the existing maturity structure for their exposure to refinancing risk. Firms whose maturing outstanding long-term debt is large are expected to be more concerned about refinancing risk. For these firms, issuing additional shorter maturities could cause a growing exposure to refinancing risk. Thus, the maturity-lengthening behavior displayed by these firms, despite the finding of previous studies (see, e.g., Hu, 2010; Gopalan et al., 2014) that they also experience a higher credit spread, suggests that refinancing risks became a first-order concern for them. In response, consistent with the theoretical prediction, these firms roll over debt maturing soon into new loans of longer maturities to minimize refinancing-risk exposure.

The identification strategy behind this baseline result relies on the variation of the maturity structure of outstanding long-term debt based on data as of year-end 2004. One might wonder, however, whether this measure is sufficiently predetermined in the sense that it is unlikely for firms to anticipate the financial crisis and restructure their outstanding long-term-debt maturity profile. If firms did that, the observed relationship would be heavily influenced by an unobserved expectation confounder: As such, the result would not entirely reflect the impact of refinancing risk. To address this concern, the same analysis is repeated using a maturity profile measured at the end of 2003, the farthest one can go back with Compustat information about the maturity structure of long-term debt. Using this alternative measure, the refinancing-risk–maturity relationship is reestimated for the sample period between August 2007 and year-end 2008.

The estimation produces results comparable with those of the first two columns. For example, the estimated coefficient reported in Column (3) shows a positive and statistically significant (at the 10% level) relationship between *Maturing/LT* and the maturity of the newly issued loans. Column (4) repeats the same analysis using the alternative measure, *Maturing/AT*, and reports that the relationship continues to be positive and significant at the 5% level. These results do not suggest that the refinancing-risk measure constructed based on 2004 data suffers from the problems mentioned above. The slight reduction in the size and statistical significance of the estimated coefficients on the refinancing-risk proxy measures computed based on the year 2003 information is not unexpected. As one goes further back in time, the association between these variables would become weaker, because some debt may retire before the scheduled due date.

Regarding firm and loan characteristics, the results reported in Table 2 show that most of the control variables assume the expected sign. Loan size is positive and statistically significantly associated with loan maturity, which is consistent with agency considerations. Among firm-level factors, maturity significantly decreases with firm size. Firms' growth options are negatively associated with maturity, which supports the agency-conflict argument. Firm profitability is positively related to loan maturity. There is some evidence that the relationship between taxes and loan maturity is negative, which is counterintuitive. As expected, asset maturity has a nonmonotonic relationship, though it is statistically insignificant.

4.3 *Multinomial Logistic Regression Analysis*

The previous regression provides evidence consistent with the view that firms with refinancing risk lengthen the maturity of their loans. There is more to be learned by investigating whether the maturities that these firms choose are in a particular maturity class along the loan maturity spectrum. For example, do they prefer one specific maturity bucket toward the long end? Or are firms, once they get maturity extension for the duration of the financial crisis, indifferent between different maturity classes. These issues are investigated using a multinomial logistic regression analysis. To this end, the loan maturities in the sample are categorized into different maturity buckets: 0–12 months, 13–36 months, 37–60 months, and more than 60 months. The multinomial-logistic-regression approach assigns one of these dependent-variable classes to be the baseline against which all other maturity classes are compared. More formally, the estimated model takes the form

$$
\begin{aligned}
ln\left(Pr(Maturity = k)/Pr(Maturity = k_B)\right) &= \alpha + \beta Refinancing\ Risk_{f,t} \\
&+ \gamma X_{f,t-1} + \eta X_{l,t} + FE_{\text{industry}} + FE_{\text{time}} + \epsilon_{l,f,t}. \quad (3)
\end{aligned}
$$

In this regression model, maturity class k_B serves as the baseline group against which maturity class k is compared. The maturity categories that the dependent variable takes are k = 0–12 months, 13–36 months, 37–60 months, or more than 60 months. The multinomial logistic regression given in Equation (3) therefore estimates the natural log of the odds of choosing a certain maturity class k ($Pr(Maturity = k)$) relative to the odds of choosing the reference maturity class k_B ($Pr(Maturity = k_B)$). Table 3 reports the estimated coefficients and marginal effects of choosing a particular maturity class relative to the baseline group (i.e., a maturity class of 0–12 months).

The reported results suggest that a greater maturing portion of outstanding long-term debt engenders greater odds of the firm choosing longer maturities than the baseline group. For example, Column (2) shows that the relative probability of choosing a maturity class of 13–36 months instead of choosing a maturity class of 0–12 months

Table 3. Multinomial Logistic Regression Analysis

This table reports results from multinomial logistic regression with the dependent variable *Maturity* taking a maturity class: 0–12 months, 13–36 months, 37–60 months, and more than 60 months. $\ln(P_{13\text{–}36}/P_{0\text{–}12})$ is the natural log of the odds of choosing a maturity class of 13–36 months relative to the odds of choosing a maturity class of 0–12 months; $\ln(P_{37\text{–}60}/P_{0\text{–}12})$ is the natural log of the odds of choosing a maturity class of 37–60 months relative to the odds of choosing a maturity class of 0–12 months; $\ln(P_{>60}/P_{0\text{–}12})$ is the natural log of the odds of choosing a maturity class more than 60 months relative to the odds of choosing a maturity class of 0–12 months. Coeff. stands for coefficient while Margin. stands for marginal effect. The main independent variable is *Maturing/LT*, denoting the proportion of maturing outstanding long-term debt scaled by total long-term debt measured based on 2004 data. Definitions of the remaining variables are provided in the appendix. In all columns, standard errors are clustered at the firm level and heteroskedastically robust. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity					
	$\ln(P_{13\text{–}36}/P_{0\text{–}12})$		$\ln(P_{37\text{–}60}/P_{0\text{–}12})$		$\ln(P_{>60}/P_{0\text{–}12})$	
	Coeff. [1]	Margin. [2]	Coeff. [3]	Margin. [4]	Coeff. [5]	Margin. [6]
Maturing/LT	1.485*	.007	1.678**	.028	2.736***	.107***
	(0.82)		(0.80)		(0.89)	
Loan Size	0.001	−.026***	0.243***	.023**	0.388***	.018**
	(0.09)		(0.09)		(0.11)	
Firm Size	−0.275**	.003	−0.383***	−.026**	−0.345***	−.004
	(0.11)		(0.10)		(0.13)	
Market-to-Book	−0.513***	−.029*	−0.348**	.008	−0.486**	−.013
	(0.17)		(0.16)		(0.22)	
Profitability	14.128***	−.224	20.277***	1.305**	20.050***	.348
	(4.19)		(4.33)		(6.18)	
Leverage	−0.545	−.059	−0.382	−.094	1.544**	.144***
	(0.64)		(0.61)		(0.72)	
Taxes	−5.663	.163	−7.238	.155	−18.826	−1.006
	(9.06)		(8.88)		(12.27)	
Rating	0.008	.001	−0.003	−.002	0.009	.001
	(0.03)		(0.02)		(0.03)	
Utility Industry	0.722*	.126	−0.271	−.076	−0.687	−.049
	(0.76)		(0.65)		(0.68)	
Asset Maturity	−0.010	−.002	0.008	.002	−0.010	−.001
	(0.02)		(0.02)		(0.02)	
$[Asset\ Maturity]^2$	0.000	.000	−0.000	−.000	−0.000	.000
	(0.00)		(0.00)		(0.00)	
Loan Type Dummy	YES	YES	YES	YES	YES	YES
Loan Purpose Dummy	YES	YES	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES	YES	YES
Time Dummy	YES	YES	YES	YES	YES	YES
N	1,272					
LR $\chi^2(99)$	1,176.45					
Pseudo R^2	0.36					

increases by 0.7% for a percentage-point increase in maturing outstanding long-term debt. Column (4) shows that a percentage-point increase in maturing outstanding long-term debt increases the probability of choosing a maturity class of 37–60 months relative to a maturity class of 0–12 months by 2.8%. However, the maturing portion of long-term debt (*Maturing/LT*) is statistically insignificant in determining the relative probabilities presented in the first and fourth columns. In contrast, Column (6) shows that firms with refinancing risk are 10.6% more likely to choose a maturity class of more than 60 months relative to a maturity class of 0–12 months for every percentage-point increase in maturing outstanding long-term debt. The highly significant marginal effects along the maturity spectrum suggest that firms with refinancing risk are more likely to choose the longest possible maturity, as exposure to refinancing risk decreases along the loan-maturity spectrum.

4.4 *Alternative Explanation: Evidence from Precrisis Periods*

One concern with the observed positive relationship may be that such pattern might not be specific to the impact of refinancing risk; but might also result from a routine maturity-choice pattern in which firms replace maturing long-term debt with new loans of longer maturity. If this alternative hypothesis is correct, then one should observe a positive relationship between the two variables irrespective of the sample periods used for the analysis—i.e., such association should be a key attribute of the data. Extending the analysis to precrisis periods could therefore be useful to better understand the primary mechanism driving the relationship. A finding of a negative relationship during a precrisis period would not support the alternative explanation. Table 4 reports the regression results from the analysis aimed at checking the validity of this alternative hypothesis using the precrisis periods 2005—July 31, 2007.

The results suggest that firms whose outstanding long-term debt maturing soon seek new loans of shorter maturities. As can be seen from the results presented in Column (1), the regression coefficient

Table 4. Alternative Explanation: Evidence from Precrisis Periods

This table reports coefficient estimates from regressions relating the maturing portion of outstanding debt to the maturity of new loans obtained during the precrisis periods. The dependent variable, *Maturity*, is the maturity of loans. Columns (1) and (2) present coefficient estimates for the sample period from 2005 to July 2007. Columns (3) and (4) report the estimated coefficients for the sample period from 2004 to July 2007. The independent variables of interest, *Maturing/LT* and *Maturing/AT*, are the proportion of maturing outstanding long-term debt scaled by total long-term debt and total assets, respectively. Definitions of the remaining variables are provided in the appendix. In all columns, standard errors (in parentheses) are clustered at the firm level and heteroskedastically robust. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity			
	As of year-end 2004 January 2005 — July 2007		As of year-end 2003 January 2004 — July 2007	
	[1]	[2]	[3]	[4]
Maturing/LT	-6.671^{***}		-4.518^{***}	
	(1.96)		(1.48)	
Maturing/AT		-11.248^{*}		-11.431^{**}
		(6.41)		(5.27)
Loan Size	2.417^{***}	2.458^{***}	2.986^{***}	2.999^{***}
	(0.45)	(0.45)	(0.38)	(0.38)
Firm Size	-0.908	-0.910	-1.169^{***}	-1.160^{**}
	(0.56)	(0.56)	(0.45)	(0.45)
Market-to-Book	-0.705	-0.686	-1.032^{*}	-1.051^{*}
	(0.67)	(0.68)	(0.56)	(0.56)
Profitability	48.899^{***}	42.685^{**}	73.091^{***}	73.105^{***}
	(14.69)	(16.94)	(14.46)	(14.41)
Leverage	3.357^{*}	4.902^{**}	2.244	3.287^{*}
	(1.90)	(1.93)	(1.82)	(1.85)
Taxes	-17.267	-12.209	-53.539^{***}	-53.991^{***}
	(25.78)	(25.79)	(17.82)	(17.76)
Rating	-0.096	-0.112	-0.174^{**}	-0.178^{**}
	(0.11)	(0.11)	(0.09)	(0.09)
Utility Industry	-4.605	-4.732	-1.116	-1.314
	(3.58)	(3.59)	(2.94)	(2.94)
Asset Maturity	0.075	0.084	0.001	0.007
	(0.06)	(0.06)	(0.05)	(0.05)
[*Asset Maturity*]^2	-0.001	-0.001	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Loan Type Dummy	YES	YES	YES	YES
Loan Purpose Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES
Time Dummy	YES	YES	YES	YES
R^2	0.272	0.270	0.319	0.319
N	3,607	3,607	4,923	4,923

for the relationship between *Maturing/LT* and the maturity of new loans is negative ($\beta = -6.67$, $S.E. = 1.96$) and statistically significant at the 1% level. This negative relationship continues to hold, though with marginal significance, when the maturing portion of long-term debt is scaled by total assets (*Maturing/AT*), as shown in Column (2). The last two columns of Table 3 repeat the above experiment using the maturing long-term debt constructed based on 2003 data and the sample period 2004—July 31, 2007. The reported results show that the maturing portion of outstanding long-term debt is negatively and significantly associated with the maturity of new loans.

Such a negative association does not support the alternative explanation. Rather, the negative relationship could potentially be explained by the fact that firms are generally less constrained in raising external debt capital in noncrisis times. Indeed there is strong evidence that supports this argument. For example, Keys et al. (2010), Purnanandam (2011) and Bord and Santos (2012) note that the increasing use of the *originate and distribute* model in which financial institutions repackage and offload loans to investors with different appetites for risk led to a considerable expansion of the supply of cheap credit in the years leading to the 2007–2009 financial crisis. This suggests that refinancing risk is less of a concern during this time. One can thus argue that firms replace maturing debt with new shorter maturities to secure rollover gains. In line with this argument, the Seta et al. (2016) model suggests that short-term financing increases the proceeds from debt rollover in good credit-market conditions.

In sum, the relationship's switch to positive during the crisis period likely reflects the change in credit-market conditions. The precrisis and postcrisis periods capture two different aspects of credit-market situations. As discussed in the introduction, the credit-market disruption during the financial crisis markedly increased concerns about the risk of limited refinancing, which undoubtedly encouraged firms to seek longer maturities.

The preceding section established a strong positive association between the maturing portion of outstanding long-term debt and the maturity of new loans obtained during the recent financial crisis, suggesting that refinancing-risk considerations are the key factor driving such associations. A natural assumption is that factors influencing the likelihood of being exposed to refinancing risk may also influence such relationships. As discussed in Section 2, firm attributes such as access to public credit markets and the availability of internally generated liquidity would create different refinancing risk effects across firms. The purpose of this section is, therefore, to investigate whether the established baseline result varies between firms classified into different groups according to these attributes. The relationship between refinancing risk and loan maturity across groups of firms is estimated using a model of the form

$$\begin{aligned} Maturity_{l,f,t} = \alpha + \beta_g \sum_{g=1}^{k} \Big(Refinancing\ Risk_{f,t} \times Group(g) \Big) \\ + \gamma X_{f,t-1} + \eta X_{l,t} + FE_{\text{industry}} + FE_{\text{time}} + \epsilon_{l,f,t}, \quad (4) \end{aligned}$$

where $Group(g)$ is an indicator variable equal 1 if a firm belongs to group g according to firm classifications based on the degree to which they access public debt markets and the level of internally generated funds. $Maturity_{l,f,t}$, $Refinancing\ Risk_{f,t}$, $X_{f,t-1}$ and $X_{l,t}$ are defined as for Equation (2). The regression includes an industry dummy (based on one digit SIC code) and a time dummy to control for industry and year effects. Standard errors are clustered at the firm level and heteroskedastically robust. The analysis are presented in the following subsections.

5.1 *Firm's Access to Public Debt Financing*

The extent to which a firm is exposed to refinancing risk may vary inversely with the firm's relative position in accessing public debt markets. As has been observed during the recent financial crisis (see, e.g., Campello et al., 2010; Chava and Purnanandam, 2011; Hale and Santos, 2013; Chiu et al., 2014), problems of refinancing risk appear to be particularly severe for firms with limited access to public debt financing. These firms may therefore be more concerned about refinancing risk. Consequently, they are expected to exhibit strong maturity-lengthening behavior to reduce their refinancing-risk exposure. The aim of this section is, therefore, to examine the question of whether refinancing-risk considerations have a differential impact on loan maturity across firms classified on the basis of the degree to which they access public debt markets.

To this end, the firms in the sample are classified on the basis of their precrisis S&P credit ratings measured at the end of June 30, 2007. The credit rating is a common measure of firms' public debt market access (see, e.g., Gilchrista and Himmelberg, 1995; Almeida et al., 2004; Sufi, 2009; Campello et al., 2010; Duchin et al., 2010; Subrahmanyam et al., 2014). Following the standard practice, this study splits firms into three groups: *No Rating* is equal to 1 if firm f has no S&P credit rating; *SG Rating* is equal to 1 if firm f has an S&P rating of BB^{+} or less; and *IG Rating* is equal to 1 if firm f has an S&P rating of BBB^{-} or more. These dummies are allowed to interact with the maturing portion of outstanding long-term debt to construct three interaction terms: *Maturing/LT* $\times$ *No Rating*, *Maturing/LT* $\times$ *SG Rating* and *Maturing/LT* $\times$ *IG Rating*. The estimation technique then involves running the maturity regression model given in Equation (4) by replacing *Refinancing Risk*$_{ft}$ $\times$ *Group*(g) with the three interaction terms constructed above. Table 5 reports the coefficient estimates from this regression.

The results show a notable difference between the three groups with respect to the impact of refinancing risk on loan maturity. As can be noted from the results reported in Column (1), the coefficient on the interaction term *Maturing/LT* $\times$ *No Rating* is statistically insignificant. This implies that an increase in the amount of outstanding long-term debt coming due soon has no effect on the maturity of new loans for firms without a credit rating. Given that refinancing-risk concerns encourage firms without credit ratings to lengthen the maturity of their loans, the finding of insignificant association may

Table 5. Refinancing risk: Firm's Access to Public Debt Finance

This table reports coefficient estimates from the regression relating the maturing portion of outstanding long-term debt to the maturity of newly issued loans during the financial crisis of 2007–2009. The dependent variable *Maturity* is the maturity of new loans in months. The main independent variable *Maturing/LT* is the maturing outstanding long-term debt scaled by total long-term debt constructed based on 2004 data. *No Rating* identifies firms without S&P credit ratings. *SG Rating* identifies firms with speculative-grade credit ratings (i.e., S&P rating BB^+ or less). *IG Rating* identifies firms with investment-grade credit ratings (i.e., S&P rating BBB^- or more). For Columns (1) and (2), S&P ratings are measured at the end of June 30, 2007. For Columns (3) and (4), it is measured at the end of December 31, 2006. Definitions of the remaining variables are provided in the appendix. In both columns, standard errors are clustered at the firm level and heteroskedastically robust. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity			
	S&P measured at the end of June 30, 2007		S&P measured at the end of December 31, 2006	
	Coeff. [1]	S.E. [2]	Coeff. [3]	S.E. [4]
Maturing/LT × *No Rating*	2.852	(3.41)	3.418	(3.29)
Maturing/LT × *SG Rating*	23.608***	(6.69)	21.343***	(6.73)
Maturing/LT × *IG Rating*	−1.645	(8.97)	5.717	(10.65)
Loan Size	2.604***	(0.72)	2.655***	(0.72)
Firm Size	−1.662*	(0.88)	−1.706*	(0.88)
Market-to-Book	−1.587*	(0.86)	−1.622*	(0.87)
Profitability	83.855***	(28.80)	83.847***	(28.74)
Leverage	−3.360	(5.17)	−3.047	(5.15)
Taxes	−56.493	(50.54)	−58.794	(50.50)
Rating	0.084	(0.20)	0.102	(0.20)
Utility Industry	−12.224	(8.43)	−11.854	(8.46)
Asset Maturity	0.030	(0.12)	0.035	(0.12)
$[Asset\ Maturity]^2$	−0.001	(0.00)	−0.001	(0.00)
Loan Type Dummy	YES		YES	
Loan Purpose Dummy	YES		YES	
Industry Dummy	YES		YES	
Time Dummy	YES		YES	
R^2	0.338		0.336	
N	1,272		1,272	
H0: The impact of *Maturing/LT* on *Maturity* is the same for *No Rating* and *SG Rating* firms.	0.004		0.013	
H0: The impact of *Maturing/LT* on *Maturity* is the same for *No Rating* and *IG Rating* firms.	0.636		0.836	
H0: The impact of *Maturing/LT* on *Maturity* is the same for SG *Rating* and *IG Rating* firms.	0.020		0.198	

suggest that these firms are unable to do so. A plausible explanation is that they are excluded from participating in the long-term credit markets, as argued by Diamond (1991).

The estimated coefficient on *Maturing/LT* $\times$ *SG Rating* is positive and significant at the 1% level. In keeping with the ex ante expectation that firms whose access to public debt markets is relatively restricted face more refinancing risk, this result shows that speculative-grade firms choose longer maturities. The negative but insignificant coefficient of the interaction term *Maturing/LT* $\times$ *IG Rating* suggests that refinancing risk has no effect on loan maturity for investment-grade firms. This finding confirms the view that refinancing risk is not a major problem for high-credit-quality firms, as they have alternative financing sources available. Indeed, Cortina-Lorente et al. (2016) provides results consistent with this argument that the debt issuance of investment-grade firms shifted away from bank loans toward public bonds during the recent financial crisis.

To determine whether the refinancing-risk effects differ across these groups, the equality of the coefficients on the interaction terms is tested. The bottom of Table 5 reports p-values associated with the chi-square (χ^2) test statistic of the equality of the interaction coefficients. As can be noted from this result, the test rejects the null hypothesis of the equality of the coefficient on *Maturing/LT* $\times$ *No Rating* and *Maturing/LT* $\times$ *SG Rating* with a p-value of 0.004. The hypothesis is also rejected when the coefficient on *Maturing/LT* $\times$ *SG Rating* is compared with that of *Maturing/LT* $\times$ *IG Rating* with a p-value of 0.02. On the other hand, the test cannot reject the null hypothesis of the equality of the coefficient on *Maturing/LT* $\times$ *No Rating* and *Maturing/LT* $\times$ *IG Rating* with a p-value of 0.636. On the basis of these tests, one can conclude that the effect of refinancing risk is more pronounced for firms with speculative-grade credit ratings. The effect is not significantly different between firms without credit ratings and those with investment-grade credit ratings.

There might be some concern with using S&P credit ratings measured at the end of June 30, 2007, as an identification strategy. A potential concern with such a proxy measure may be that firms anticipate the financial crisis and change their financing, investment and risk-management policies. For example, Bolton et al. (2013) develop a theoretical model that predicts that firms that anticipate the threat of a future financial crisis postpone investments and payout decisions. Thus, one might argue that these policy adjustments may affect the firms' future maturity choices and their immediate credit ratings. If that is the case, the estimated results could be biased because of confounding factors. In that case, one would expect to observe results that are different from the results presented above when credit ratings are measured earlier in time. To address this concern, and also to gauge the performance of the S&P measure based on June 30, 2007, data as an identification tool, this study replicates the analysis in Column (1) using S&P credit ratings measured at the end of December 31, 2006.

The regression results reported in Column (3) of Table 5 somewhat reaffirm the significant difference in the maturity effect of refinancing risk across rating groups observed in the preceding column. For example, the coefficient of the interaction term *Maturing/LT* $\times$ *SG Rating* continues to be highly significant. On the other hand, the coefficient on *Maturing/LT* $\times$ *IG Rating* is still statistically indistinguishable from zero, though it changes its sign to positive. The estimated coefficient on *Maturing/LT* $\times$ *No Rating* is now marginally significant. However, according to the comparability tests of the interaction coefficients reported at the bottom of Table 5, one can continue to reject the null hypothesis of the equality of the coefficients on *Maturing/LT* $\times$ *No Rating* and *Maturing/LT* $\times$ *SG Rating*. Whereas one now fails to reject the equality of the coefficients on *Maturing/LT* $\times$ *SG Rating* and *Maturing/LT* $\times$ *IG Rating*.

5.2 *Firm's Internal Financial Constraints*

Recently emerging literature strongly suggests that firms that face higher internal financial constraints—i.e., limited level of internal funds—are more likely to be exposed to refinancing risk. Given the baseline result that firms with refinancing risk choose longer maturities, one would expect such preference for longer maturities to occur more among firms that face greater internal financial constraints. Therefore, the empirical analysis in this section is aimed at investigating how the maturity effect of refinancing risk varies across different groups of firms categorized according to the internal financial constrains they face.

In line with the discussion in Section 2, and also as in Cleary et al. (2007) and Guariglia (2008), this study uses cash flows as a measure of internal financial constrains. Accordingly, the firms in the sample are sorted into three groups based on average quarterly cash flows scaled by total assets measured in 2006 (Quarter 1 to Quarter 4). Three dummy variables are constructed: *Low Cash Flow* identifies those firms whose cash flows fall in the lower tercile of the cash-flow distribution of all firms. *Medium Cash Flow* identifies firms with cash flows that fall in the middle tercile of the cash-flow distribution of all firms. *High Cash Flow* identifies firms whose cash flows fall in the upper tercile of the cash flow distribution. These dummy variables interacted with the maturing portion of outstanding long-term debt scaled by total long-term debt. The regression model given in Equation (4) is then estimated by replacing $\textit{Refinancing Risk}_{f,t} \times \textit{Group}(g)$ with the three interaction terms. Table 6 displays the results obtained.

The result shows that the maturity effect of refinancing risk varies in the cross-section of firms sorted on the basis of their cash flows. As the results reported in Column (1) shows, the coefficient estimate on the interaction term *Maturing/LT* $\times$ *Low Cash Flow* is positive and statistically significant at the 1% level. This suggests that maturing long-term debt is associated with an increase in the maturity of newly issued loans for firms with low cash flows. This result is consistent with the finding of Choi et al. (2013) that low-cash-flow firms disperse the maturity structure of their debt. A number of scenarios could explain this result. One plausible explanation is that the negative or near-zero cash flows these firms maintain leaves them with insufficient funds for debt service. In this situation, choosing shorter maturities would mean, as debt retires at a higher frequency, magnifying the refinancing costs and risk that they already face. This can explain why they choose longer maturities.

Table 6. Refinancing Risk: Firm's Internal Financial Constraints

This table reports results from models probing whether the effect of refinancing risk varies across firms classified by the internal financial constraints they face. The dependent variable, *Maturity*, is the maturity of new loans measured in months. The main independent variable of interest, *Maturing/LT*, is the proportion of maturing outstanding long-term debt scaled by total long-term debt computed based on 2004 data. *Low Cash Flow* identifies firms with cash flows in the lower tercile of the cash-flow distribution of all firms. *Medium Cash Flow* identifies firms whose cash flows fall in the middle tercile of the cash-flow distribution of all firms. *High Cash Flow* identifies firms with cash flows in the upper tercile of the cash-flow distribution. Cash flows are average cash flows scaled by total assets. For Column (1), cash flows are measured in 2006 (average of Quarter 1 to Quarter 4). For Column (3), cash flows are measured in 2005 (average of Quarter 1 to Quarter 4). In both columns, standard errors are clustered at the firm level and heteroskedastically robust. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity			
	Cash flows measured in 2006 (average of Q1 to Q4)		Cash flows measured in 2005 (average of Q1 to Q4)	
	Coeff. [1]	S.E. [2]	Coeff. [3]	S.E. [4]
Maturing/LT × *Low Cash Flow*	25.288***	(9.176)	29.558***	(10.131)
Maturing/LT × *Medium Cash Flow*	8.518*	(4.647)	7.026	(5.340)
Maturing/LT × *High Cash Flow*	5.869	(3.992)	3.557	(3.912)
Loan Size	2.784***	(0.757)	2.793***	(0.788)
Firm Size	−1.830*	(0.934)	−2.090**	(0.983)
Market-to-Book	−1.349	(0.864)	−1.276	(0.887)
Profitability	72.734**	(30.130)	101.123***	(34.126)
Leverage	−0.649	(5.367)	−3.608	(5.338)
Taxes	−47.093	(52.163)	−117.231	(73.639)
Rating	0.047	(0.195)	0.015	(0.200)
Utility Industry	−13.258	(8.434)	−14.302*	(8.627)
Asset Maturity	0.026	(0.120)	0.042	(0.126)
$[\textit{Asset Maturity}]^2$	−0.001	(0.001)	−0.001	(0.001)
Loan Type Dummy	YES		YES	
Loan Purpose Dummy	YES		YES	
Industry Dummy	YES		YES	
Time Dummy	YES		YES	
R^2	0.338		0.338	
N	1,205		1,180	
H0: The impact of *Maturing/LT* on *Maturity* is the same for *Low* and *Medium Cash Flow* firms.	0.092		0.042	
H0: The impact of *Maturing/LT* on *Maturity* is the same for *Low* and *High Cash Flow* firms.	0.043		0.014	
H0: The impact of *Maturing/LT* on *Maturity* is the same for *Medium* and *High Cash Flow* firms.	0.648		0.576	

Another possible explanation can be derived from the finding of Cleary et al. (2007). These authors argue that firms with negative cash flows need to raise large funds not only to close a financing gap, but also to make a large investment that generates sufficient cash flows to cove debt service for the creditors to be willing to offer funds in the first place. Higher debt ratios lower the firms' debt capacity, which in turn, exacerbates their refinancing risk even further. The finding of a positive association is therefore consistent with the argument forwarded by Sun (2014) that firms borrow with longer maturities to preserve their debt capacity.

One may, however, appeal to the finding of previous studies that low-cash-flow firms maintain cash reserves as a liquidity buffer (Bates et al., 1958), and that firms use cash holdings to absorb rollover losses (Harford et al., 2014), and argue that firms with low cash flows can still borrow at shorter maturities. While these firms might make such maturity decisions, it is, however, important to note that they cannot do so without ultimately exposing themselves to refinancing risk. The main reason is that, in the presence of maturing outstanding debt, additional shorter maturities will drain internal savings for those firms with negative or close to zero cash flows.

Another result presented in Column (1) is that, while the estimated coefficient of the interaction term *Maturing/LT* $\times$ *Medium Cash Flow* is marginally significant, the estimated coefficient of the interaction term *Maturing/LT* $\times$ *High Cash Flow* is not statistically distinguishable from zero. This result suggests that maturing outstanding long-term debt has no effect on the maturity of new loans issued by firms with high cash flows. This is perhaps because the high cash flows that firms maintain allows them to absorb any rollover losses. Consequently, they may not seek longer-maturity debt.

To investigate whether the refinancing-risk effects differ among these firms, the analysis next compares the estimated coefficients of the three interaction terms. The bottom of Table 6 reports p-values associated with χ^2 test statistic. As one can note from the reported results, the test rejects the null hypothesis of the equality of the coefficients on the interaction terms *Maturing/LT* $\times$ *Low Cash Flow* and *Maturing/LT* $\times$ *Medium Cash Flow* with a p-value of 0.09. The null hypothesis of the equality of the coefficients on the interaction terms *Maturing/LT* $\times$ *Low Cash Flow* and *Maturing/LT* $\times$ *High Cash Flow* is also rejected with a p-value of 0.04. In contrast, the test cannot reject the null hypothesis of the equality of the estimated coefficients on the interaction terms *Maturing/LT* $\times$ *Medium Cash Flow* and *Maturing/LT* $\times$ *High Cash Flow* with a p-value of 0.65. On the basis of the comparability tests of the interaction-term coefficients, one would conclude that the effect is more pronounced for low-cash-flow firms while the maturity effect of refinancing risk is very similar for firms with medium and high cash flows.

To gauge the performance of the cash flows measured based on 2006 data as an identification tool, Column (3) repeats the analysis by splitting the firms in the sample on the basis of their average quarterly cash flows scaled by total assets measured in 2005 (Quarter 1 to Quarter 4). As can be seen from the reported results, the estimated coefficient on *Maturing/LT* $\times$ *Low Cash Flow* continues to be highly significant, whereas the coefficient on *Maturing/LT* $\times$ *High Cash Flow* remains insignificant. The only change is that the interaction term *Maturing/LT* $\times$ *Medium Cash Flow* has now a statistically insignificant coefficient. The p-values associated with the test of the equality of the coefficients reported at the bottom of Table 6 also show that the test continues to reject the null hypothesis that the coefficient on the interaction term *Maturing/LT* $\times$ *Low Cash Flow* is comparable with that on *Maturing/LT* $\times$ *Medium Cash Flow*. Again, the test fails to reject the null hypothesis of the equality of the coefficients on *Maturing/LT* $\times$ *Medium Cash Flow* and *Maturing/LT* $\times$ *High Cash Flow*.

6 REFINANCING RISK: LENDING RELATIONSHIP WITH CREDITORS

An emerging body of literature on relationship lending emphasizes the importance of bank–firm relationships as an important credit-constraint alleviating factor, especially during crises. Therefore, this section investigates whether building lending relationships with creditors benefits firms with refinancing risk by offering longer maturities during periods of financial crises. Such analysis requires distinguishing among loan facilities based on the existence of a firm's lending relationship with creditors. In the literature on relationship lending, firms' repeated interactions with their previous lenders are commonly used as a sorting device (see, e.g., Dahiya et al., 2003; Bharath et al., 2007, 2011; Gopalan et al., 2011). Following this literature, the current analysis uses previous firm–lender interactions to split the loan facilities in the sample into relationship and nonrelationship loans. The analysis is then performed by running split-sample regression—i.e., regressing a loan maturity equation for each group separately. Table 7 reports the regression results.

From the results reported in Column (1), the regression coefficient for the relationship between *Maturing/LT* and the maturity of new loans is significant (at the 1% level) within the sample of relationship loans. This significant relationship continues to hold when alternative measure *Maturing/AT* is used, as shown in Column (2). The last two columns of Table 7 repeat the same exercise using the sample of nonrelationship loan facilities. In contrast to the results reported in the first three columns, Columns (4) and (5) show that the estimated coefficients on *Maturing/LT* and *Maturing/AT* are not statistically distinct from zero. The result that an increase in refinancing risk is associated with an increase in the maturity of the loans obtained from relationship lenders is consistent with the view that relationship lenders help their borrowers in crisis times.

To examine whether the effect is significantly greater in the sample of relationship loans, the analysis compares the estimated coefficients of *Maturing/LT* and *Maturing/AT* within relationship and nonrelationship loans. The bottom of Table 7 reports p-values corresponding to the z test statistic for the difference between the two regression coefficients. While refinancing risk has a significant effect on loan maturity within the sample of relationship loans, the test however cannot reject the null hypothesis of the equality of the coefficients on refinancing risk within the samples of relationship and nonrelationship loans. Thus, one could not conclude that the refinancing-risk effect is significant.

A standard result in the relationship-lending literature is that firms who use one bank tend to have stronger relationships than do firms

Table 7. Refinancing Risk: Lending Relationship with Creditors

Maturity is the dependent variable. The independent variables are *Maturing/LT* and *Maturing/AT*. *Weak Relation*, *Medium Relation* and *Strong Relationship* identify facilities obtained from lenders with whom the borrowers have lending relationships that fall in the lower, middle and upper terciles of the distribution of lending interactions of all firms, respectively. Columns (1)–(3) present results obtained from the sample of relationship loans. Columns (4) and (5) report results from nonrelationship loans. In addition to the reported variables, the regressions also control for taxes, rating, utility industry, asset maturity and square of asset maturity. In all columns, standard errors (in parentheses) are clustered at the firm level and are heteroskedastically robust. The *t*-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity				
	Relationship loan			Nonrelationship loan	
	[1]	[2]	[3]	[4]	[5]
Maturing/LT	9.411***			5.492	
	(3.40)			(6.23)	
Maturing/AT		34.909***			36.396
		(9.28)			(27.02)
Maturing/LT × *Weak Relation*			16.354***		
			(5.62)		
Maturing/LT × *Medium Relation*			9.012		
			(5.91)		
Maturing/LT × *Strong Relationship*		4.849			
			(4.66)		
Loan Size	3.060***	2.898***	3.041***	1.946	1.901
	(0.83)	(0.82)	(0.83)	(1.26)	(1.25)
Firm Size	−2.083**	−1.928**	−2.091**	−1.887	−1.841
	(0.95)	(0.93)	(0.95)	(1.80)	(1.80)
Market-to-Book	−2.907**	−2.663**	−2.830**	−2.745	−2.755
	(1.18)	(1.16)	(1.18)	(2.23)	(2.22)
Profitability	150.667***	140.576***	151.466***	88.595*	86.712
	(51.24)	(50.77)	(51.48)	(52.41)	(52.69)
Leverage	−0.768	−2.959	−1.390	−6.067	−8.576
	(5.67)	(5.57)	(5.62)	(9.33)	(9.39)
Loan Type Dummy	YES	YES	YES	YES	YES
Loan Purpose Dummy	YES	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES	YES
Time Dummy	YES	YES	YES	YES	YES
R^2	0.485	0.490	0.486	0.279	0.282
N	656	656	656	432	432
H0: The impact of *Maturing/LT* on *Maturity* is the same in Columns (1) and (4).	0.547				
H0: The impact of *Maturing/AT* on *Maturity* is the same in Columns (2) and (5).		0.954			
H0: The impact of *Maturing/LT* on *Maturity* is the same for *Weak Relation* and *Medium Relation*.			0.372		
H0: The impact of *Maturing/LT* on *Maturity* is the same for *Weak* and *Strong Relationship*.			0.101		
H0: The impact of *Maturing/LT* on *Maturity* is the same for *Medium* and *Strong Relationship*.			0.542		

relying on multiple banks (see, e.g., Detragiache et al., 2000; Farinha and Santos, 2002). Accordingly, a further analysis is performed to investigate whether the maturity effect of refinancing risk varies between firms with different degrees of lending relationships with creditors. To this end, three dummy variables are constructed based on the number of repeated firm–lender interactions: *Weak Relation* identifies loan facilities for which the borrowers' lending relationships with creditors fall in the lower tercile of the distribution of all firm's lending interactions. *Medium Relation* identifies facilities obtained from lenders with whom the borrowers have lending relationships that fall in the middle tercile. *Strong Relationship* identifies loan facilities that firms have received from lenders with whom they have lending relationships that fall in the upper tercile of the distribution of lending interactions for all firms. These dummy variables are allowed to interact with the maturing portion of outstanding long-term debt to create three interaction terms, which are used to replace $\textit{Refinancing Risk}_{f,t} \times \textit{Group}(g)$ in Equation (4).

The results from running such a regression model are displayed in Column (3) of Table 7. As can be seen from the reported results, while the estimated coefficients on *Maturing/LT* × *Weak Relation* is statistically significant, the interaction term *Maturing/LT* × *Medium Relation* and *Maturing/LT* × *Strong Relationship* are insignificantly estimated. This result is unexpected. The test reported at the bottom of Table 7 however cannot reject the null hypothesis of equal coefficients on the three interaction terms. Thus, one cannot conclude that the effect is significantly more pronounced in loan facilities in which the firms have weak relationships with the creditors.

7 ADDITIONAL ROBUSTNESS CHECK

So far, this analysis has conducted robustness checks of the baseline results to an alternative measure of refinancing risk and an alternative interpretation. Nevertheless, there may still exist some potential concerns related to sample selection and estimation specification. To address these concerns, this section reports two additional robustness checks.

7.1 *Sample-Selection Bias*

One of the potential concerns with the analysis in this article is related to the problem of sample-selection bias. The problem is that information on loan facilities is observed only for those firms that obtain loans during the crisis; it is not observed for firms that obtain loans during precrisis periods and not during the financial crisis. Some firms that obtain loans during precrisis periods may be credit rationed (even if they would like to borrow) and are excluded from participating in the credit markets during the financial crisis. This type of selection might bias the conclusion if those firms that would normally take short-term loans—perhaps because they are informationally opaque and, hence, need to be closely monitored—are the ones that are credit rationed. More precisely, such selection may put an upward pressure on the effect of refinancing on the maturity of loans.

To address this concern, this article follows Almeida et al. (2012) and uses matching-estimation approaches developed in the literature to mitigate this type of selection bias due to observables. To this end, firms' potential for exposure to refinancing risk based on the maturing portion of outstanding long-term debt is used to sort firms into *treated* and *untreated* groups. Matching then involves identifying control firms (i.e., firms that do not have a large fraction of maturing long-term debt and, hence, do not need to roll over maturing debt) from the untreated groups that best match the treated firm (i.e., firms that have a large fraction of maturing long-term debt and, hence, have more potential for refinancing risk). This method allows comparison of firms that are identical in all aspects except for the portion of maturing outstanding long-term debt. Thus, any difference in the maturity of new loans between the two most-closely matched groups can be attributed to the effect of refinancing risk.

Table 8. Robustness Check of Sample-Selection Bias: Evidence from Mahalanobis Matching

This table reports results from the Mahalanobis-matching technique. The dependent variable is *Maturity*, measured in months. Panel A sorts firms into the treated group whose maturing outstanding long-term debt out of total long-term debt, measured in 2004, is greater than 10%. In Panel B, the treated firms are defined as those for which the maturing portion of outstanding long-term debt, measured in 2004, is greater than 20%. The *nearest neighbor* estimator calculates the difference in loan maturity between each treated loan and n untreated loans that have the closest Mahalanobis distance. *ATT* denotes the average treatment on the treated. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Treated obs.	Untreated obs.	*ATT*	
			Coeff.	S.E.
	[1]	[2]	[3]	
Panel A: Treated if *Maturing/LT* > 10%				
One to one	425	847	6.33***	(1.66)
Nearest neighbors ($n = 10$)	425	847	6.33***	(1.66)
Nearest neighbors ($n = 50$)	425	847	6.33***	(1.77)
Panel B: Treated if *Maturing/LT* > 20%				
One-to-one	206	1,066	6.55***	(1.89)
Nearest neighbors ($n = 10$)	206	1,066	6.55***	(2.32)
Nearest neighbors ($n = 50$)	206	1,066	6.55***	(2.43)

To identify control firms, this study employs the Mahalanobis matching technique described by Cochran and Rubin (1973) and Rubin (1980). In this covariate-based matching method, control firms are selected on the basis of their Mahalanobis-distance metric from the treated firms. A number of loan and firm characteristics are used to match firms in the two groups. These include loan size, firm size, profitability, market to book, leverage, credit rating, taxes and asset maturity. The study uses the *nearest neighbor* matching estimator to implement the matching techniques. This estimator calculates the difference in the maturity of new loans between the two groups for which the Mahalanobis-distance matrix is minimal. The matching results are displayed in Table 8.

In Panel A, the treated firms are defined as those for which the maturing portion of outstanding long-term debt is greater than 10% while firms whose maturing long-term debt is less than 10% are considered as untreated. As can be seen from Column (3), the one-to-one estimator produces the average treatment effect on the treated (*ATT*) of 6.3. Increasing the number of firms used as the control group (n) does not affect the result. For example, for $n = 10$ and $n = 50$, the nearest-neighbor estimator reports the *ATT* of 6.3. Panel B repeats the same analysis by focusing on firms whose maturing outstanding long-term debt out of total long-term debt is greater than 20%. As can be seen from the table, the *ATT* for the one-to-one estimator is 6.6. For the nearest-neighbor estimator, the *ATT* is also 6.6 whether $n = 10$ or $n = 50$. This matching analysis demonstrates that those firms that have a large proportion of maturing long-term debt during the financial crisis obtain longer maturities than otherwise-similar firms, except for the amount of long-term debt coming due. One can thus conclude from this analysis that the baseline result survives even after correcting for a sample-selection bias.

7.2 *Bank Fixed Effect*

Another potential concern is associated with the creditor-level heterogeneity in terms of the maturity of loans. Agency-based theories of corporate maturity choice suggest that creditors can use debt maturity to control agency-related problems. The more the agency conflicts between creditors and firms, the more creditors want to use shorter maturities to control firms. Conversely, creditors having less agency friction with firms may less urgently need shorter maturities as a disciplining device. It is possible that such heterogeneity across lenders may affect the maturity of the loans they offer. To check the robustness of the baseline regression results to this variation, this section reestimates the maturity regression model while controlling for lender fixed effects through the use of lender dummies. Table 9 reports the results from this regression specification.

Inclusion of the lender-level fixed-effect dummy does not affect the estimated coefficients much when compared to the results reported in Table 2.[4] As Column (1) displays, the estimated coefficient on *Maturing/LT* is still statistically significant (at the 5% level). Column

4 Note that there are fewer observations in Table 9 than in Table 2 because of missing information on the identity of some lenders. Hence, one cannot directly compare the results reported in the two tables.

Table 9. Robustness Check: Bank Fixed Effect

This table presents coefficient estimates from regressions relating the maturing portion of outstanding debt and the maturity of new loans obtained during the 2007–2009 financial crisis. The dependent variable, *Maturity*, is the maturity of loans in months. The independent variable of interest, *Maturing/LT*, is the proportion of maturing outstanding long-term debt scaled by total long-term debt measured in year 2004. Column (1) reports the coefficient estimates obtained from a regression that includes the lender-fixed-effect dummy and clusters the standard errors at the firm level. Column (2) presents results obtained from a regression that clusters standard errors at the firm and lender level. Column (3) reports results obtained from a regression that includes the lender-fixed-effect dummy and clusters the standard errors at the firm and lender level. Definitions of the remaining variables are provided in the appendix. In all columns, standard errors are heteroskedastically robust. The t-test of significance is *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Maturity					
	Lender FE		Clust. by lender and firm		Lender FE, clust. by firm and lender	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
	[1]		[2]		[3]	
Maturing/LT	8.623**	(3.58)	8.324**	(3.41)	8.623**	(3.49)
Loan Size	3.324***	(0.68)	2.769***	(0.72)	3.324***	(0.63)
Firm Size	−2.194**	(0.93)	−1.775*	(0.98)	−2.194*	(1.13)
Market-to-Book	−1.265	(0.88)	−1.684*	(0.99)	−1.265	(1.11)
Profitability	108.299***	(33.39)	83.253***	(28.00)	108.299***	(28.16)
Leverage	−3.347	(4.73)	−1.706	(5.18)	−3.347	(4.52)
Taxes	−32.638	(70.45)	−54.439	(48.24)	−32.638	(62.48)
Rating	0.091	(0.18)	0.048	(0.18)	0.091	(0.15)
Utility Industry	0.942	(3.97)	−11.550	(9.29)	0.942	(3.84)
Asset Maturity	0.023	(0.12)	0.039	(0.12)	0.023	(0.11)
$[Asset\ Maturity]^2$	−0.001	(0.00)	−0.001	(0.00)	−0.001	(0.00)
Loan Type Dummy	YES		YES		YES	
Loan Purpose Dummy	YES		YES		YES	
Industry Dummy	YES		YES		YES	
Time Dummy	YES		YES		YES	
Lender Fixed Effect	YES		No		YES	
R^2	0.604		0.331		0.604	
N	1,269		1,269		1,269	

(2) presents results from a regression specification that clusters standard errors at the firm and lender levels. As the result shows, such clustering does not make the coefficient estimate of *Maturing/LT* statistically less significant. Column (3) estimates a regression that includes the lender-level fixed-effect dummy and clusters the standard errors by firm and lender, and obtains similar results. Evidently, the baseline regression result is robust to this alternative specification.

8 CONCLUDING REMARKS

This study explores whether refinancing risk is an important determinant of debt-maturity choice. To do so, the analysis in this paper investigates how firms with a potential for exposure to refinancing risk choose the maturity of new loans they obtain during the 2007–2009 financial crisis. To address concerns related to endogeneity, firms' exposure to refinancing risk is predetermined using the maturity profile of long-term debt outstanding in year 2004 and that comes due during the financial crisis. The evidence shows that an increase in the amount of maturing outstanding long-term debt is associated with new loans of longer maturities. This result is consistent with theories that promote the view that, in the presence of refinancing risk, firms choose longer maturities because longer maturities help to mitigate refinancing-risk exposure.

The maturity effect of refinancing risk is stronger for firms with speculative-grade credit ratings. This result can be understood in the context of recent evidence that firms with limited access to public debt markets are more exposed to negative credit-supply shocks. Expectedly, this encourages speculative-grade firms to extend the maturity of their debt. Consistent with the view that firms with limited internally generated funds are more likely to be exposed to more refinancing losses because their debt is more risky, the effect is more pronounced for firms that maintain low cash flows. Furthermore, there is also evidence that firms with refinancing risk obtain longer maturities from their relationship lenders.

While the result is robust to an alternative measure of refinancing risk, an estimation technique that accounts for sample-selection bias and alternative specifications, one caveat of this study is that firms' equity issues are omitted from the analysis. Thus, one direction of future research is to investigate the sensitivity of the baseline result to equity choices. Reestimating the analysis in this paper using public debt, which has larger maturity than bank loans used in this study, also appears promising.

REFERENCES

Acharya, V. V., Gale, D., and Yorulmazer, T. (2011). Rollover risk and market freezes. *Journal of Finance*, 66:1177–1209.

Almeida, H., Campello, M., Laranjeira, B., and Weisbenner, S. (2012). Corporate debt maturity and the real effects of the 2007 credit crisis. *Critical Finance Review*, 1:3–58.

Almeida, H., Campello, M., and Weisbach, M. (2004). The cash flow sensitivity of cash. *Journal of Finance*, 59:1777–1804.

Barclay, M. J. and Smith, C. W. (1995). The maturity structure of corporate debt. *Journal of Finance*, 50:609–631.

Barnea, A., Haugen, R. A., and Senbet, L. W. (1980). A rationale for debt maturity structure and call provisions in the agency theoretic framework. *Journal of Finance*, 35:1223–1234.

Bates, T., Kahle, K., and Stulz, R. (1958). Why do u.s. firms hold so much more cash than they used to? *Journal of Finance*, 64:1985–2021.

Benmelech, E., Bergman, N., and Seru, A. (2015). Financing labor. *NBER Working Paper No. 17144*.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S., and Miller, N. H. (2005). Debt maturity, risk, and asymmetric information. *Journal of Finance*, 60:2895–2923.

Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A. (2007). So what do i get? the bank's view of lending relationships. *Journal of Financial Economics*, 85:368–419.

Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A. (2011). Lending relationships and loan contract terms. *Review of Economic Studies*, 24:1141–1203.

Billett, M. T., King, T.-H. D., and Mauer, D. C. (2007). Growth opportunities and the choice of leverage, debt maturity, and covenants. *Journal of Finance*, 62:697–730.

Bolton, P., Chen, H., and Wang, N. (2013). Market timing, investment, and risk management. *Journal of Financial Economics*, 109:40–62.

Bolton, P., Freixas, X., Gambacorta, L., and Mistrulli, P. E. (2016). Relationship and transaction lending in a crisis. *Review of Financial Studies*, 29:2643–2676.

Bord, V. and Santos, J. A. (2012). The rise of the originate-to-distribute model and the role of banks in financial intermediation. *Economic Policy Review*, 18:21–34.

Brick, I. E. and Ravid, S. A. (1985). On the relevance of debt maturity structure. *Journal of Finance*, 40:1423–1437.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives*, 33:77–100.

Brunnermeier, M. K. and Yogo, M. (2009). A note on liquidity risk management. *American Economic Review*, 99:578–83.

Butler, A. W., Grullon, G., and Weston, J. (2006). Can managers successfully time the maturity structure of their debt issues? *Journal of Finance*, 61:1731–1758.

Campello, M., Giambona, E., Graham, J. R., and Harvey, C. R. (2011). Liquidity management and corporate investment during a financial crisis. *The Review of Financial Studies*, 24:1944–1979.

Campello, M., Graham, J. R., and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97:470–487.

Chava, S. and Purnanandam, A. (2011). The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics*, 99:116–135.

Chava, S. and Roberts, M. R. (2008). How does financing impact investment? the role of debt covenants. *Journal of Finance*, 63:2085 – 2121.

Chen, H., Xu, Y., and Jun, Y. (2012). Systematic risk, debt maturity, and the term structure of credit spreads. *NBER Working Paper 18367*.

Cheng, I.-H. and Milbradt, K. (2012). The hazards of debt: Rollover freezes, incentives, and bailouts. *Review of Financial Studies*, 25:1070–1110.

Chiu, W.-C., Peña, J. I., and Wang, C.-W. (2014). Financial crises, financing sources, and default risks. *Available at SSRN: http://ssrn.com/abstract=2513756 or http://dx.doi.org/10.2139/ssrn.2513756*.

Choi, J., Hackbarth, D., and Zechner, J. (2013). Granularity of corporate debt. *CFS Working Paper, No. 2013/26*.

Chui, M., Domanski, D., Kugler, P., and Shek, J. (2010). The collapse of international bank finance during the crisis: evidence from syndicated loan markets. *BIS Quarterly Review*, September:39–49.

Cleary, S., Povel, P., and Raith, M. (2007). The u-shaped investment curve: Theory and evidence. *Journal of Financial & Quantitative Analysis*, 42:1–39.

Cochran, W. G. and Rubin, D. B. (1973). Controlling bias in observational studies: A review. *Sankhyā: The Indian Journal of Statistics, Series A*, 35:417–446.

Cortina-Lorente, J. J., Didier, T., and Schmukle, S. L. (2016). How long is the maturity of corporate borrowing? evidence from bond and loan issuances across markets. *WB, Policy Research Working Papers 7815*.

Covitz, D. M., Liang, N., and Suarez, G. A. (2013). The evolution of a financial crisis: Collapse of the asset-backed commercial paper market. *Journal of Finance*, 68:815–848.

Dahiya, S., Saunders, A., and Srinivasan, A. (2003). Financial distress and bank lending relationships. *Journal of Finance*, 58:375–399.

Dennis, S., Nandy, D., and Sharpe, I. G. (2000). The determinants of contract terms in bank revolving credit agreements. *Journal of Financial and Quantitative Analysis*, 35:87–110.

Detragiache, E., Garella, P., and Guiso, L. (2000). Multiple versus single banking relationships: Theory and evidence. *Journal of Finance*, 55:1133–1161.

Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *Quarterly Journal of Economics*, 106:709–737.

Duchin, R., Ozbas, O., and Sensoy, B. A. (2010). Costly external ïňĄ-nance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97:418–435.

Farinha, L. A. and Santos, J. A. (2002). Switching from single to multiple bank lending relationships: Determinants and implications. *Journal of Financial Intermediation*, 11:124–151.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. *Journal of Finance*, 41:19–37.

Froot, K. A., Scharfstein, D. S., and Stein, J. C. (1993). Risk management: Coordinating corporate investment and financing policies. *Journal of Finance*, 48:1629–1658.

Gilchrista, S. and Himmelberg, C. P. (1995). Evidence on the role of cash flow for investment. *Journal of Monetary Economics*, 36:541–572.

Gobbi, G. and Sette, E. (2014). Do firms benefit from concentrating their borrowing? evidence from the great recession. *Review of Finance*, 18:527–560.

González, V. M. (2015). The financial crisis and corporate debt maturity: The role of banking structure. *Journal of Corporate Finance*, 35:310–328.

Gopalan, R., Song, F., and Yerramilli, V. (2014). Debt maturity structure and credit quality. *Journal of Financial and Quantitative Analysis*, 49:817–842.

Gopalan, R., Udell, G. F., and Yerramilli, V. (2011). Why do firms form new banking relationships? *Journal of Financial and Quantitative Analysis*, 46:1335–1365.

Gorton, G. and Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, 104:425–451.

Gorton, G. B. (2009). Slapped in the face by the invisible hand: Banking and the panic of 2007. *Prepared for the Federal Reserve Bank of Atlanta's 2009 Financial Markets Conference: Financial Innovation and Crisis, May 11-13.*

Goswami, G. (2000). Asset maturity, debt covenants, and debt maturity choice. *The Financial Review*, 35:51–68.

Grossman, S. J. and Hart, O. D. (1982). Corporate financial structure and managerial incentives. *The Economics of Information and Uncertainty, edited by John McCall. Chicago: University of Chicago Press*.

Guariglia, A. (2008). Internal financial constraints, external financial constraints, and investment choice: Evidence from a panel of uk firms. *Journal of Banking & Finance*, 32:1795–1809.

Guedes, J. and Opler, T. (1996). The determinants of the maturity of corporate debt issues. *Journal of Finance*, 51:1809–1833.

Hainz, C. and Wiegand, M. (2013). How does relationship banking influence credit financing? evidence from the financial crisis. *Ifo Working Paper, No. 157*.

Hale, G. and Santos, J. A. C. (2013). Do banks propagate debt market shocks?

Harford, J., Klasa, S., and Maxwell, W. F. (2014). Refinancing risk and cash holdings. *Journal of Finance*, 69:975–1012.

He, Z. and Milbradt, K. (2016). Dynamic debt maturity. *Review of Financial Studies*, 29:2677–2736.

He, Z. and Xiong, W. (2012a). Rollover risk and credit risk. *Journal of Finance*, 67:391–429.

He, Z. and Xiong, W. (2012b). Dynamic debt runs. *Review of Financial Studies*, 25:1799–1843.

Hu, X. (2010). Rollover risk and credit spreads in the financial crisis of 2008.

Ivashina, V. and Scharfstein, D. S. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97:319–338.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3:305–360.

Johnson, S. A. (2003). Debt maturity and the effects of growth opportunities and liquidity risk on leverage. *Review of Financial Studies*, 16:209–236.

Jun, S.-G. and Jen, F. C. (2003). Trade-off model of debt maturity structure. *Review of Quantitative Finance and Accounting*, 20:5–34.

Kane, A., Marcus, A. J., and McDonald, R. L. (1985). Debt policy and the rate of return premium to leverage. *Journal of Financial and Quantitative Analysis*, 20:479–499.

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

Kwan, S. H. (2010). Financial crisis and bank lending. *Federal Reserve Bank of San Francisco, Working Paper 2010-11*.

Leland, H. E. (1998). Agency costs, risk management, and capital structure. *Journal of Finance*, 53:1213–1243.

Leland, H. E. and Toft, K. B. (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *Journal of Finance*, 51:987–1019.

Li, B. (2013). Refinancing risk, managerial risk shifting, and debt covenants: An empirical analysis. *Queen's University*.

Mian, A. R. and Santos, J. A. C. (2011). Liquidity risk, and maturity management over the credit cycle. *University of California, Berkeley, Working Paper*.

Mitchell, K. (1993). The debt maturity choice: An empirical investigation. *Journal of Financial Research*, 16:309–320.

Morris, J. (1992). Factors affecting the maturity structure of corporate debt. *Working paper, University of Colorado at Denver*.

Morris, S. and Shin, H. S. (2016). Illiquidity component of credit risk—the 2015 lawrence r. klein lecture. *International Economic Review*, 57:1135–1148.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5:147–175.

Paligorova, T. and Santos, J. A. C. (2016). Banks' exposure to rollover risk and the maturity of corporate loans. *Review of Finance*, doi: 10.1093/rof/rfw039:1–27.

Puri, M., Rocholl, J., and Steffen, S. (2011). Global retail lending in the aftermath of the us financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics*, 100:556–578.

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

Rubin, D. B. (1980). Bias reduction using mahalanobis-metric matching. *Biometrics*, 36:293–298.

Schmidt, L., Timmermann, A., and Wermers, R. (2016). Runs on money market mutual funds. *American Economic Review*, 106:2625–2657.

Schroth, E., Suarez, G. A., and Taylor, L. A. (2014). Dynamic debt runs and financial fragility: Evidence from the 2007 abcp crisis. *Journal of Financial Economics*, 112:164–189.

Seta, M. D., Morellec, E., and Zucchi, F. (2016). Rollover traps. *Swiss Finance Institute Research Paper No. 16–19*.

Shleifer, A. and Vishny, R. W. (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives*, 25:29–48.

Smith, C. W. J. and Warner, J. B. (1979). On financial contracting: An analysis of bond covenants. *Journal of Financial Economics*, 7:117–161.

Subrahmanyam, M. G., Tang, D. Y., and Wang, S. Q. (2014). Credit default swaps and corporate cash holdings. *CFS Working Paper, No. 462*.

Sufi, A. (2009). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *Review of Financial Studies*, 22:1659–1691.

Sun, Q. (2014). Cash holdings and risky access to future credit. *mimeo, University of Southern California*.

Szkup, M. (2013). Optimal debt maturity structure, rollover risk and strategic uncertainty. *mimeo, New York University*.

Taggart, R. A. J. (1977). A model of corporate financing decisions. *Journal of Finance*, 32:1467–1484.

Valenzuela, P. (2015). Rollover risk and credit spreads: Evidence from international corporate bonds. *Review of Finance*, 20:631–661.

Xu, Q. (2016). Early refinancing and maturity management in the corporate bond market. *Available at SSRN: https://ssrn.com/abstract=2787968*.

Appendix: Variable Definitions

Table 10. **Variable Definitions**

Variable	Definition
Maturing/LT	The ratio of long-term debt that becomes due in one, two, three, four and five year scaled by total long-term debt based on data in 2003.
Maturing/AT	The ratio of long-term debt that becomes due in one, two, three, four and five year scaled by total assets based on data in 2003.
Maturity	The number of months from facility start date to facility end date
Loan Size	The natural logarithm of loan facility amount in million
Term Loan	A dummy variable taking the value one if the loan type is term loan
Revolver	A dummy variable taking the value one if the loan type is revolver
364-Day Facility	A dummy variable taking the value one if the loan type is 364-day facility
Other Type	A dummy variable taking the value one if the loan type is other
Corporate Purpose	A dummy variable taking the value one if the loan purpose is corporate purpose
Working Capital	A dummy variable taking the value one if the loan purpose is working capital
Takeover	A dummy variable taking the value one if the if loan purpose is for takeover
Debt Repay	A dummy variable taking the value one if the loan purpose is for debt repayment
Other Purpose	A dummy variable taking the value one if the loan purpose is for others
Relationship	A dummy taking the value one if the loan is issued by relationship lender
Weak Relation	A dummy taking the value one facilities for which the borrowers lending relationships with creditors fall in the lower tercile of the distribution of all firm's lending interactions
Medium Relation	A dummy taking the value one facilities for which the borrowers lending relationships with creditors fall in the middle tercile of the distribution of all firm's lending interactions
Strong Relationship	A dummy taking the value one facilities for which the borrowers lending relationships with creditors fall in the upper tercile of the distribution of all firm's lending interactions
Firm Size	The natural logarithm of the book value of total assets
Profitability	The ratio of earnings before interest, taxes, depreciation and amortization to the book value of total assets
Leverage	The ratio of total debt (which is the sum of debt in current liability and long-term debt) to the book value of total assets
Market-to-Book	The ratio of book value of total asset minus book value of equity plus market value of equity to book value of total asset
Rating	A dummy variable taking the value one if the firm has standard and poor's long-term issuer rating

(Continued on next page)

Table 21. Variable Definitions (Continued)

Variable	Definition
IG Rating	A dummy variable taking the value one if the firm's S&P credit rating is "BBB-" or above
SG Rating	A dummy variable taking the value one if the firm's S&P credit rating is "BB+" or below
Utility Industry	A dummy variable taking the value one if the firm is in the utility industry
Asset Maturity	The ratio of net property, plant, and equipment to depreciation expenses
Cash Flow	The ratio of quarterly cash flows to the book value of total assets
Low Cash Flow	A dummy variable taking the value one for firms whose cash flows fall in the lower tercile of the cash flow distribution of all firms
Medium Cash Flow	A dummy variable taking the value one for firms whose cash flows fall in the middle tercile of the cash flow distribution of all firms
High Cash Flow	A dummy variable taking the value one for firms whose cash flows fall in the upper tercile of the cash flow distribution
Taxes	The ratio of total tax payment scaled by total assets

Essay Two

3

Syndicated Lending: The Role of Relationships for the Retained Share

1 INTRODUCTION

Syndicated lending arrangements have become a major source of external corporate finance (Dennis and Mullineaux, 2000; Chui et al., 2010). An interesting element of such a multilender financing arrangement is that it involves aspects of relationship lending. That is, lead arrangers often have lending relationships with the firms (Bharath et al., 2007; Gadanecza et al., 2012; Akiyoshi and Minamihashi, 2014), while syndicate participants essentially engage in an arm's-length transaction. Through this relationship, lead arrangers can learn the firm's inside information that may be unavailable to the other lenders. However, such access to a firm's soft information has raised concerns about whether the information asymmetry creates arranger–participant agency conflicts (Jones et al., 2005; Panyagometh and Roberts, 2010; Gadanecza et al., 2012). The literature predicts that the role of relationships in fostering the lead arranger's particular behavior has consequences for the share it retains in the loan. The literature's prediction on the impact of lending relationships on the retained share is less clear.

The predictions are associated with the tasks of screening and monitoring firms, which traditionally occupy a central position in the theory of financial intermediation (see, e.g., Townsend, 1979; Campbell and Kracaw, 1980; Diamond, 1984; Williamson, 1987). With regard to this, syndicated lending may be viewed as a special contractual arrangement mainly in the sense that these tasks are delegated to lead arrangers instead of being executed by members of a syndicate as a team. A very classic benefit of the delegation of such activities is that of avoiding the duplication of costs and free-riding associated with multiple creditors (Holmstrom, 1982; Diamond, 1984; Krasa and Villamil, 1992; Welch and Bris, 2005). Coupling syndication, in which the lead arrangers retain less than 100% of the claim on the loan, with delegation may, however, erode the lead arranger's incentive to efficiently perform the tasks in accordance with participants' best interests. To limit such a dilution of incentives—i.e., a potential drift toward a diverging interest in pursuit of private benefits—participants request the lead arranger to contribute a larger share than the lead arranger would otherwise prefer to hold for optimal risk diversification.

One prediction emphasizes the role of relationships as fostering commitment to monitoring, which enables lead arrangers to hold a smaller share. The argument here is that firms require some level of monitoring for the information-compatibility constraints to be satisfied (Diamond, 1984; Dye, 1986; Demski and Sappington, 1987; Baliga, 1999). Monitoring borrowers, however, involves nonzero costs, suggesting that the lead arrangers' monitoring quality is a function of costly investments made in monitoring. As a delegated monitor, lead arrangers bear the entire monitoring costs while only a fraction of the monitoring benefits accrue to them. The reduction of the benefit is not unproblematic and may encourage shirking. Hence, for a lead arranger to choose an optimal monitoring effort in a way that is socially beneficial to syndicate members, monitoring must be cheap. By lowering the costs of producing firm-specific information (Haubrich, 1989; Petersen, 1999; Boot, 2000), lending relationships enhance monitoring efforts. With increased monitoring activities and the accompanying amelioration of agency conflicts, participants are encouraged to buy more of the loan.

A competing prediction in the banking literature emphasizes the perspective that relationships facilitate lead arrangers' exploitation of syndicate participants (e.g., Sharpe, 1990; Rajan, 1992; Schenone, 2010). In the context of syndicated lending, one could argue that lead arrangers may pursue self-interest in their syndication activities, perhaps because they have outstanding loans with the firm or they care about long-term business relationships. As such, the risk of exploitation becomes high in syndicate arrangements in which informational discrepancies between members are greater. The dissemination of an information memorandum—which contains details about the borrower and the transaction—during the syndication process may thus be construed as the lead arranger's attempt to remove the discrepancies. However, one cannot expect lead arrangers to divulge the entire soft information about their borrowers simply because it could invite a profit-dissipating competition that affects their ability to capture firms in long-term relationships and extract the associated relationship rent (Von Thadden, 1995; Boot and Thakor, 2000; Schenone, 2010). With less information about the firm, participants are unwilling to buy more of the loan, as they rationally anticipate that lead arrangers may take advantage of their information superiority by syndicating out low-quality loans.

This paper's objective is to help resolve these conflicting hypotheses by empirically examining the association between a lead arranger's relationship with a firm and its retained share in the loan to that firm. These competing views, however, may not be mutually exclusive, and the agency-conflict-reducing and information-exploitation-facilitating features of a lending relationship could operate simultaneously. In this case, the result could be interpreted that one feature of a lending relationship is more important than the other. The analysis is conducted using syndicated loans made to nonfinancial U.S. firms. Following the argument maintained in the theoretical literature that relationships emanate from repeated interactions, the present study measures lending relationships by tracking the history of lending interactions between lead arrangers and their borrowers.

The analysis shows that relationships are negatively and significantly related to the share retained by lead arrangers. This negative empirical association suggests that lead arrangers retain a smaller share when syndicated loans are made to firms with whom they have a prior relationship. Therefore, it can be argued that participants believe the agency-problem-alleviating feature of a lending relationship outweighs the information-exploitation-facilitating aspect. As such, they do not require relationship lead arrangers to hold a substantial fraction of financial stakes to fend off the temptation to become lenient in their screening and monitoring tasks. The reduction in the retained share is also economically nonnegligible. A prior lending relationship reduces the retained share by 8.1%.

The analysis further provides new evidence that the reduction in the retained share is more pronounced in syndicated arrangements headed by lead arrangers whose reputation lies at the bottom of the lead arrangers' reputation spectrum. The variation of the impact of lending relationships on the retained share with a lead arranger's reputation can be understood in light of the theory of corporate reputation advanced by Diamond (1989, 1991), Schaffer (1989), Hirshleifer and Thakor (1992) and Chemmanur and Fulghieri (1994). In the context of syndicated lending, the implication of this literature is that lead arrangers seeking to maintain their reputation restrain themselves from skimping on screening and monitoring. Such self-restraining behavior makes the importance of relationships less relevant. This finding is reinforced by the fact that the reduction of the retained share is stronger for small lead arrangers.

Further analysis shows that the effect of lending relationships on the retained share is not limited to certain syndicated contract arrangements with a particular class of borrowers. That is, the negative retained-share effect is at work irrespective of how borrowing firms are grouped—i.e., whether they are sorted into opaque–transparent, small–large, or speculative–nonspeculative groups. Of particular interest is a reduction in the retained share in loans made to informationally opaque firms, small firms, and firms with low ratings.

This is interesting simply because these are classes of firms for which monitoring is expected to be intensive, and, hence, at greater risk for agency problems. While the result does not provide evidence that the effect is stronger in loans made to some class of borrowers than the others, the analysis does, however, document that the effect of lending relationships on the retained share is more pronounced in loan contracts that include covenants than those that do not.

The results of this analysis are subjected to different robustness checks to address some potential concerns. One concern is related to endogeneity, which could stem from the possible nonrandom match between a lead arranger and a borrowing firm. One might argue that the endogeneity problem confounds the effect of lending relationships and results in erroneous conclusions. To check this estimation-related concern, the present study employees two estimation methods. Using Mahalanobis and propensity-score matching methods (Rubin, 1973, 1980; Rosenbaum and Rubin, 1983; Heckman et al., 1997, 1998), this paper presents results that are qualitatively comparable to estimates from ordinary least squares (OLS) regressions. Additionally, working with binary endogenous treatment models (Heckman, 1978; Maddala, 1983; Wooldridge, 2002), the result is also robust to the control of unobservable (and observable) factors that could affect lead-arranger–borrower relationship formation. With these robustness results, the endogeneity problems appear less important.

However, other concerns may still stem from the procedure adopted to construct a relationship measure. One concern is related to the presence of multiple lead arrangers in a syndicated loan, which would increase the likelihood of the loan being organized by a relationship lead arranger. By estimating the effect of lending relationships on the retained share in a sample of facilities arranged by a single lead arranger, this paper observes that the previous results continue to hold.

With the above results, the present study contributes to a recently growing literature that investigates the impact of lending relationships in syndicated financing arrangements. Often the focus of these empirical studies is to examine the impact of lending relationships on syndicated contract terms. Some of this literature establishes a positive association between lending relationships and loan amount (e.g., Bharath et al., 2011), suggesting that previously built lending relationships enable firms to obtain a large loan amount. Other studies establish a negative link between relationships and syndicated loan pricing (e.g., Bharath et al., 2011; Alexandre et al., 2014), suggesting that building relationships with lenders helps firms obtain less expensive loans. The present study departs from this literature by investigating how lending relationships affect the retained-share aspect of the syndicated loan structure. The analysis adds to the above mentioned literature by showing that establishing relationships with firms enable lead arrangers to retain a smaller share in loans to one firm.

2 THEORETICAL ARGUMENTS AND EMPIRICAL PREDICTIONS

2.1 *Why Syndicate Loans?*

The theoretical perspectives in the finance literature offer an array of rationales for loan syndication. One popular rationale behind the formation of an intercreditor lending alliance may be called the *risk-exposure-diversification rationale*. This rationale emphasizes the risk-sharing motive as the explanation for lenders' involvement in cooperative teams (Wilson, 1968; Amershi and Stoeckenius, 1983; Chowdhry and Nanda, 1983; Schure et al., 2005). This motive emerges when a creditor's internal prudential lending model restrains the lender's willingness to take up the entire amount of the loan. In such situations, syndication can endogenously arise as an intercreditors' club in which a loan is allotted among the syndicate members. By permitting the division of risks associated with a loan, syndication enables lenders that have inadequate risk tolerance to reduce their exposure to the risks. Empirically, this risk-sharing-based argument appears to explain the formation of a syndicate (see, e.g., Lockett and Wright, 2001; Brander et al., 2002, in the context of venture capital).

Another rationale for lenders to come together may be called the *capital-adequacy-requirement rationale*. This argument holds that a lender is unable to take up the entire amount of a particular loan. Constraints could arise when the size of a loan exceeds the amount a single lender is able to provide (Nitani and Riding, 2013). Thus capital constraints can foster lenders' interests in the establishment of an intercreditor consortium through which they can raise the necessary funds. Lenders could also be constrained by regulations that limit the size of a loan a lender makes to a firm. In this situation, a syndicate facilitates financing too large for a single lender. Empirically, the capital-constraint-based perspective also appears to have wide support (see, e.g., Simons, 1993; Jones et al., 2005).

The other rationale for the formation of a syndicated arrangement may be called the *specialization rationale*. The literature argues that lenders tend to specialize their activities based on the different functions they perform (Benston, 1994; Santos, 1998; Das and Nanda, 1999). Since large loans presumably involve the design of complex contractual terms, and perhaps also require joint monitoring of collateral and covenants, syndication might thus be sought to bring together lenders with the necessary expertise. Syndicate formation can thus be attributed to the lead arranger's desire to influence the mix of the syndicate members' skills and competencies. This can be justified on efficiency grounds: The formation of a syndicate can offer an arrangement in which lenders use their comparative advantages to enhance loan performance. Empirically, François and Missonier-Piera (2007) provide evidence of how specialization affects the structure of loan syndication by influencing coagent selection.

Expanding relationship networks can also provide another rationale for involvement in loan syndication. Involvement in syndicated loans gives borrowing firms greater exposure to a large number of lenders. One potential benefit from such exposure is that it enables firms to establish multiple relationships that introduce competition among lenders, thereby curbing rent extractions associated with a single relationship lender (Von Thadden, 1995; Detragiache et al., 2000; Gopalan et al., 2011b). From the standpoint of participating lenders, studies show that young and inexperienced lenders participate in syndicated loans to gain know-how transfer from experienced lead arrangers (Tykvová, 2007). Involvement in syndicated lending would thus introduce these participants to new business areas and industrial sectors they may not otherwise enter due to a lack of proper arranging know-how and expertise.

2.2 *Syndication Process and Lead-Arranger Award Mechanisms*

The process by which a borrower and a group of lenders enter into a syndicated credit agreement is initiated in different ways (Allen, 1990; Esty, 2001). In most syndicated loan arrangements, the process begins with the prospective borrowers, who use different mechanisms by which they award the leadership role. One such mechanism might be called *competitive bidding*—a process by which lenders that possess the necessary execution competence in syndicated finance submit proposals. The borrower then awards the mandate of organizing a syndicate to the lender (or lenders) with the most favorable terms. Another method of awarding the lead-arranger mandate is *negotiation*, which is often used when the borrowers decide to contact and appoint a particular lender or group of lenders. The syndication process can also be initiated by the lead arrangers. In either case, after receiving the mandate, the lead arranger will negotiate with the borrower and enter into a preliminary agreement on the contract terms.

The mandated lead arrangers can undertake the syndication activities in different ways (Allen, 1990; Esty, 2001; Armstrong, 2003). One way is to organize a syndicate on a *fully underwritten* basis. That is, lead arrangers agree to provide the entire loan amount and subsequently invite potential participating lenders to syndicate out the loan. This form of syndication, however, involves a syndication risk mainly in the sense that the lead arrangers will be compelled to keep on their balance sheets the remaining loan amounts that are not financed by the participants. Lead arrangers can also undertake the syndication activity on a *best-effort* basis. That is, the lead arranger agrees to finance a fraction of the loan and works to bring together participants willing to fund the remainder of the loan.

The composition of that group is influenced by the complexity involved in the transaction and the underlying rationale for syndication. The available evidence shows that lead arrangers choose participating lenders geographically close to the borrower when intensive monitoring is required (Sufi, 2007). As the level of the required monitoring becomes less intensive, lead arrangers increasingly include foreign participants in the composition (Lim et al., 2014). Research also shows that loan renegotiations and restructuring are common features of private loan (e.g., bank loan) agreements (Roberts and Sufi, 2009b), suggesting that this consideration may also influence the number of participants. In this regard, one would expect lead arrangers to choose a more dispersed syndicate (i.e., increase the number of participants) when they want to make renegotiation more difficult so as to reduce the borrower's strategic default incentives (Gertner and Scharfstein, 1991; Bolton and Scharfstein, 1996).

A prior lending relationship may influence a borrowing firm's lead-arranger choice. That is, a relationship may affect the lead-arranger award mechanisms in that it may encourage (especially) troubled borrowing firms to appoint a lead arranger through negotiations with existing relational lenders who may share common interests with the borrower and are likely to have strong incentives to shirk.[1] This creates some concern for participants because, in a typical syndicated loan arrangement, the lead arranger owes no fiduciary responsibilities to the participants (Qu, 2000; Ryan, 2009).[2] This concern may also be stoked further as participant lenders may not observe the lead arranger's screening and monitoring activities, which is in line with

1 In fact, previous lending relationships can also confer competitive advantage on relational lenders by enabling them to design specific transaction terms that are appropriate for the firm and also acceptable to participants. In this way, previous lending relationships can help win the lead-arranger mandate and the substantial compensation fees for organizing a syndicated loan (Gadanecz, 2004; Berg et al., 2016).

2 Lead arrangers normally assume the role of an agent after syndicating out a loan. Therefore, it follows that the lead arranger should owe fiduciary obligations to the participants. But in a syndicated arrangement, the lead arranger often includes certain clauses that preclude the lead arranger from acting as a fiduciary to the participant lenders.

the imperfect monitoring model mentioned by Holmstrom (1979). Since monitoring the monitor (i.e., the lead arranger) cannot be done at zero cost, no individual syndicate member would be prepared to bear monitoring costs to conduct the monitoring. It is also hard to expect the formation of an *ad hoc* committee to monitor the monitor because of the well-established serious coordination and motivation problems associated with team formation.

2.3 *Lead Arrangers' Retained Share*

The syndication literature (see, e.g., Jones et al., 2005; Sufi, 2007; Panyagometh and Roberts, 2010) portrays a lead arranger's shirking behavior as stemming from insufficient internal motivating factors. This literature thus maintains that a lead arranger's retained share serves as an incentive for contract compliance and suggests that syndicates should be structured such that the lead arranger retains a share in the loan. Such structure is expected to be dictated to a great extent by the participants' level of concern, which stems largely from information asymmetries.

The above perspective is in the spirit of the informed–uninformed-investor theory advanced by Leland and Pyle (1977). In the context of syndicated lending, this literature implies that relatively informed lead arrangers should retain a share in the loan to alleviate agency concerns and thereby encourage participants to join the syndicate. Retaining an especially large share can initiate a contractually induced self-deterring incentive on the part of those lead arrangers who might otherwise be predisposed to wrongdoing with respect to screening and monitoring. This follows primarily because the increased retained share also increases the cost of shirking borne by the lead arranger. In essence, a retained share can serve as a lead arranger's signaling instrument that the lead arranger's incentives are aligned with those of the participating lenders. A conclusion from this discussion is that participants can use the share retained by lead arranger to control the lead arranger's shirking motives.

One would expect that when the agency-conflict-moderating feature of a lending relationship predominates, syndicated arrangements headed by lead arrangers who have lending relationships with the firm should be more attractive to participants. Such an aspect of a lending relationship dictates against requiring lead arrangers to hold a large financial stake in the loan. One would thus expect to observe a negative empirical link between the share retained by lead arrangers and their lending relationship with the firm. In contrast, when the information-exploitation-facilitating aspect of a lending relationship outweighs other features, syndicated-loan arrangements whose lead arrangers have lending relationships with the borrowers should be less attractive to potential participants. With the increased wrongdoing implied by this aspect of a lending relationship, participants would respond by requiring the lead arranger to take on a larger fraction of the loan. This suggests a positive empirical association between lending relationships and the retained share. In essence, the impact of lending relationships on the retained share depends on the relative feature balance of the lending relationship in the syndicated-loan market.

2.4 *Lead Arrangers' Reputation*

The syndication literature (see, e.g., Sufi, 2007; Ivashina, 2009; Cai, 2010) also argues that a lead arranger's reputation serves as a non-contractual device to deter lead arrangers' opportunistic wrongdoings. As such, a lead arranger's reputation certifies to potential participants that the lead arranger is credible in implementing mechanisms that attenuate conflicts of interest that may impact participants. This argument is consistent with the evidence that lead arrangers' reputation is significantly associated with improved borrower performance subsequent to loan syndication (Ross, 2010; Bushman and Wittenberg-Moerman, 2012).

There are several good reasons why reputational concerns could induce lead arrangers not to shirk. One explanation is related to the fact that the syndicated-loan market involves considerable reciprocity (Cai, 2010). That is, it is highly probable for the lead arranger of a current syndicated loan to be involved as a participant in future syndicated loans arranged by its current participants. This reciprocal arrangement could create a two-way disciplining process by which participants can credibly threat to punish those lead arrangers with bad reputations by not inviting them to loans they arrange. In anticipation of the loss of rents associated with participating in syndicated loans, lead arrangers would refrain from taking actions that impair their reputation.

The other explanation is likely associated with the very fact that loan syndication is a team-lending activity: The success of a syndicate is closely tied to the existence of stable interlender networks (Champagne and Kryzanowski, 2007; Godlewski et al., 2012). The literature contends that maintaining the stability of the intercreditor network depends on lenders' reputation in financial markets (Pichler and Wilhelm, 2001). This suggests that events that damage a lead arranger's reputation—such as the borrowing firm declaring bankruptcy (Gopalan et al., 2011a) and corporate fraud (Wang et al., 2010)—introduce instability to the intercreditor network. The consequence may be reputational problems for lead arrangers, and, as a result, with a fractured lead–participant past alliance may experience difficulty in finding new lenders willing to participate in subsequent syndicates organized by the same lead arranger. In essence, considerations about preserving previous lead–participant alliances offer lead arrangers self-disciplining incentives to keep their reputation untarnished.

The literature, however, maintains that reputation has a threshold mainly in the sense that reputational concerns have effects for lenders with greater reputation (Chemmanur and Fulghieri, 1994; Ordoñez, 2013; Chaudhry and Kleimeier, 2013). It therefore follows that reputational concerns should present strong motivational incentives for lead arrangers who have reputation at the very top of the lead arrangers' reputational spectrum. Since more reputable lead arrangers have a high reputational stake attached to the performance of the syndicated loans, a loss of reputation has a substantial effect on them. One would thus expect considerations of losing reputation to motivate reputable lead arrangers to commit to due diligent screening and more intensive monitoring. Such commitment to avoid lenient behavior, in turn, facilitates loan syndication activities, as supported by empirical studies that suggesting that reputable lead arrangers sell off more of their loans (Dennis and Mullineaux, 2000; Sufi, 2007; Demiroglu and James, 2010) at low interest rates (Ivashina, 2009; Ross, 2010). The present study thus expects the lead arranger's reputation to weaken the empirical association between lending relationships and the retained share.

2.5 *Informationally Opaque and Transparent Firms*

The literature argues that a firm's information environment affects the degree to which syndicate participants face agency problems. The widespread perspective in the corporate-governance literature is that firms with publicly available information are more likely to be subjected to the scrutiny of outside investors (Shleifer and Vishny, 1997). One would thus expect participants to be exposed to fewer agency problems in a sample of syndicate arrangements with transparent firms. In contrast, opaque firms have only limited exposure to outsiders' scrutiny that might discipline the management because, for firms with limited publicly available information, high transaction and information costs makes monitoring by outsiders more difficult (Demsetz and Lehn, 1985). This may suggest that participants are more likely to face the classic agency problems identified by Jensen and Meckling (1976) in a sample of syndicated arrangements with opaque firms. Participants should therefore benefit more from lead arrangers' monitoring, which means that a firm's information environment influences the need to provide lead arrangers with monitoring incentives through the retained share.

Several previous studies have examined the degree to which the availability of information (or lack thereof) about the borrower is an important determinant of the retained-share aspect of the syndicated-loan structure. The available evidence is broadly consistent with the above theoretical predictions in that it documents a sharp difference between the retained share in a loan to opaque and transparent firms. Some have found that the probability of syndicating a loan increases as the borrower becomes informationally more transparent (Dennis and Mullineaux, 2000; Jones et al., 2005; Panyagometh and Roberts, 2010). Others have found that lead arrangers retain a larger share and form a more concentrated syndicate when the borrower is informationally opaque (Bosch and Steffen, 2007; Sufi, 2007; Chaudhry and Kleimeier, 2013). A plausible explanation behind these empirical regularities would be that opacity exacerbates the participants' incentive conflicts, which exist on both side of the loan contract.

The above literature thus shows that participants are clearly more concerned with loans to opaque than transparent firms. But one would expect participants not to require relationship lead arrangers to retain a larger share, simply because they have already acquired knowledge of the borrower, which reduces the necessary monitoring costs and thereby mitigates the risks of shirking. The literature, however, is less clear about whether relationships have similar or differential effects on the retained share in loans to opaque and transparent firms.

2.6 *Covenanted Loans*

A large body of the corporate-finance literature show that, in a manner consistent with the prediction of the theory of incomplete financial contracting, lenders impose covenants in loan contracts. Covenants are restrictions incorporated into contracts designed to curb the borrowers' incentives to expropriate wealth from lenders by prohibiting them from taking actions that facilitate the transfer of the lenders' wealth (Jensen and Meckling, 1976; Smith and Warner, 1979). Any violation of the loan covenants may therefore suggest that the borrower is not complying with the imposed restriction. In fact, a covenant breach is often considered a technical default (Beneish and Press, 1993, 1995). Since covenants normally allocate control rights between lenders and borrowers on a state-contingent basis (Berlin and Mester, 1992; Gârleanu and Zwiebel, 2009), upon the violation of covenants control rights shift to the lenders.

The shift of control rights justifies the lenders' intervention in corporate decisions when triggered by covenant violations. The available evidence shows that lenders often find it optimal to waive the consequences of covenant violations or renegotiate the initial contracts rather than enforce the covenants by terminating the loan agreement (Chen and Wei, 1993; Denis and Wang, 2014). Nevertheless, a growing number of studies show that such lenders' intervention has serious consequences for the firm's financing (Roberts and Sufi, 2009a), investment (Chava and Roberts, 2008) and governance policies (Nini et al., 2012). Borrowers' considerations when facing these consequences expectedly induce them to develop self-disciplining behavior, which mitigates one layer of agency problems in loan syndication. One can thus argue that participants are exposed to fewer agency problems in contractual arrangements that impose covenants.

However, since covenants are often based on noisy indicators of the firm's true financial health, studies suggest that more intensive monitoring of the firm's compliance with the imposed restrictions is required to determine the real cause of the covenant violation (Berlin and Loeys, 1988). As the empirical literature documents, covenants are often set tightly in loan agreements, so near the violation threshold that they are easily breached (Smith, 1993; DeFond and Jiambalvo, 1994; Chava and Roberts, 2008). It thus follows that a covenant violation may not necessarily indicate that the borrower is extracting wealth from the lender. This suggests that contracts that impose covenants require monitoring in the first place. Hence, in the context of syndicated loans, agency conflicts might be even more acute in arrangements in which contracts include covenants. Since relationship lead arrangers have monitoring-cost advantages, participants may not demand they take on a larger fraction of the loan.

3 DATA, MEASUREMENTS AND PRELIMINARY ANALYSIS

3.1 *Sources and Sample Selection*

This analysis is based on information gathered from various data sources. The information on syndicated loans is extracted from the DealScan database. This data file provides detailed information on contract terms, such as the amount and maturity of the loan, the type and purpose of the loan, the loan-facility origination date and covenants. DealScan also provides information on the identity of the lenders offering the financing and some information on the identity of the borrowers, including the borrower's name, geographic location, parent and ultimate parent ID, standard industrial classification (SIC), and sales at close. DealScan, however, has limited accounting information. Thus, the borrower's and lead arranger's financial information is extracted from the Compustat database. To avoid the loan arrangements affecting the accounting information, the Compustat variables used correspond to the end of the year prior to the loan-agreement date.

A problem with combining information from DealScan and Compustat is the lack of a common identifying code between the two datasets. The present study thus uses the DealScan–Compustat link table constructed by Michael Roberts and Wharton Research Data Services[3] to merge the information collected from the two data sources. This link table combines the two data files on the basis of the borrowing firms' names. Loans for which the corresponding financial information of the firm is absent using this link are excluded from the analysis.

The sample construction begins with all loan facilities in the combined data file. Following previous empirical studies, loans made to firms in the financial industry (i.e., firms with SIC code between 6000 and 6999) are excluded from the sample. Since the interest of this analysis is syndicated loans, all loan facilities distributed by non-syndication methods are removed from the sample. This paper also

3 See Chava and Roberts (2008) for details on the DealScan–Compustat link table.

requires that the loan be made to a U.S. firm and be initiated between 1987 and 2013. A further restriction is also imposed by removing from the sample all facilities that do not include information on the lead arranger. The few loan facilities for which the borrowing firms report negative values for their sales at close are also excluded from the sample. This process of cleaning the data yields a sample containing 43,651 syndicated loan facilities.

3.2 *Measuring Lead Arrangers' Retained Share*

The dependent variable of interest is the share retained by lead arrangers, and the DealScan data provides information on the allocation made by some lenders. However, prior to using this variable, it is important to determine whether the lender in a loan facility is the lead arranger or a participating lender. DealScan contains a field that describes the role of the lenders, Lead Arranger Credit, that takes the values *Yes* or *No* for each lender. This study uses this field to classify lenders such that a lender is designated as a lead arranger if the Lead Arranger Credit field takes the value *Yes*, and as a participant lender if the field takes the value *No*. This method of sorting lenders into lead and participant groups is consistent with the procedure used by previous studies (see, e.g., Bharath et al., 2007, 2011). After lenders are sorted, the allocations made by the lead arrangers are used as the dependent variable. For syndicated loans headed by multiple lead arrangers, the retained share at a facility level is calculated as the average of the proportion held by each lead arranger.

3.3 *Measuring Lending Relationships*

Information on whether the borrowers obtain loans from lenders with whom they have previous lending relationships is not available in the DealScan database. The measure of a lending relationship therefore needs to be constructed. The theoretical relationship literature (e.g., Haubrich, 1989; Petersen, 1999; Boot, 2000) appears to be instructive in this regard. This literature argues that lending relationships are built over time through engagements involving repeated interactions between a firm and a lender. This theoretical guidance is closely followed in the present study to construct a lending-relationship measure. Indeed, the repeated interaction argument is central to what now appears to be a standard methodology for measuring lending relationships in the strand of research that combines the literature on lending relationships and loan syndication (see, e.g., Dahiya et al., 2003; Schenone, 2004; Bharath et al., 2007, 2011).

The procedure adopted in this study involves tracking the history of previous interactions between the lead arranger and the borrower of a loan to identify whether they are involved in lending interactions in the past. Since the sample in this study has a median loan maturity of 57 months, the present study uses a five-year history window to search for previous lending interactions. It is also important to note that the sample is left-tail trimmed. That is, the first loan facility of any borrower has no prior loan experience. Thus, to avoid erroneously sorting the first loan of all borrowers into a relationship or nonrelationship group, this study excludes the first loan of each borrower from the analysis. Following this procedure, three lending-relationship measures are constructed for each loan facility.

One measure of lending relationships is denoted by *Relation Binary*. This dummy is constructed to identify whether a lending relationship exists between the lead arranger of a current loan and the borrowing firm in the last five years. Accordingly, the dummy variable takes the value one if the lead arranger and the firm engaged in lending interactions in the past and zero otherwise. For syndicated loan facilities involving more than one lead arranger, the indicator variable takes the value one if at least one lead arranger interacted with the borrower in the past.

The other measures are constructed to reflect the intensity of previous lending interactions. *Relation Number* is constructed by dividing the number of loans that a lead arranger, i, has lent to a borrower, j, in the last five years by the total number of loans that the borrower, j, has taken over the same time period. To show how this number-based measure is computed using the DealScan data, let $(N)_t^{i \to j}$ denote the number of times lead arranger i has organized loans for borrower j as of time t. Likewise, let $(N)_t^{\text{all}\to j}$ denote the number of times that all lead arrangers have lent to borrower j as of time t. Then, the number-based measure of lending relationships between lead arranger i and borrower j as of loan facility l is given as

$$\textit{Relation Number}_{i,j,l} = \sum_{t-1}^{t-5} (N)_t^{i\to j} \Big/ \sum_{t-1}^{t-5} (N)_t^{\text{all}\to j}. \tag{5}$$

The other measure, *Relation Amount*, is computed by dividing the sum of the amounts of loans that lead arranger i has lent to borrower j in the last five years by the total amount of loans that borrower j has borrowed during the same period. To represent this idea in a formula, let $(A)_t^{i\to j}$ denote the amount that lead arranger i has made to borrower j as of time t. Again, let $(A)_t^{\text{all}\to j}$ denote the amount borrower j has borrowed from all lenders in the same period. The amount-based measure of prior lending relationships between lead arranger i and borrower j at a time when they enter into a new agreement for loan facility l is given by

$$\textit{Relation Amount}_{i,j,l} = \sum_{t-1}^{t-5} (A)_t^{i\to j} \Big/ \sum_{t-1}^{t-5} (A)_t^{\text{all}\to j} \tag{6}$$

The values that *Relation Number* and *Relation Amount* take range from zero to one. Zero indicates the absence of lending interactions prior to the current loan. One corresponds to a situation where the borrower engaged in lending interaction only with the lead arranger of the current loan. Thus, larger values of the measures correspond to more intensive involvement in lending relationships. For syndicated loan facilities in which multiple lead arrangers are involved, this study allows the measures to take the largest value, the value corresponding to the lead arranger with whom the borrower is most involved in lending relationships.

3.4 *Measuring Lead Arrangers' Reputation*

A commonly employed methodology in the empirical syndication literature to measure a lead arranger's reputation is to use the lead arranger's previous market share in the loan-syndication market (see, e.g., Bharath et al., 2007; Sufi, 2007). Computing a lead arranger's market share involves dividing the sum the amount of syndicated loans arranged by the lead arranger at a given time by the total amount of syndicated loans arranged by all lead arrangers in the same period. Following these studies, the present paper also applies the same methodology. For arrangements in which more than one lead arranger organizes the syndicate, this paper shares the loan amount equally among the lead arrangers and then calculate the market share for each. To compute the market share using the DealScan data, let LA^i_{lt} denote the amount of syndicated loan l arranged by lead arranger i at time t. The market share, $Market\ Share_{i,t}$ for lead arranger i at time t is then given as

$$Market\ Share_{i,t} = \sum_{l}^{L}(LA)^i_{lt} \bigg/ \sum_{i}^{I}\sum_{l}^{L}(LA)^i_{lt} \tag{7}$$

For each time period, the market share given by the above equation reflects the proportion of syndicated loans arranged by a particular lead arranger. The numerator of the right-hand term aggregates the dollar value of syndicated loans (where $l = 1, \ldots, L$) that lead arranger i arranged at time t. The denominator aggregates the dollar amount of all syndicated loans organized by all lead arrangers (where $i = 1, \ldots, I$) at time t.

After the market share is computed, lead arrangers are then ranked according to their market share. The ranking helps to identify top-tier lead arrangers, those that dominate the syndicated-loan market. It is becoming a tradition in the empirical literature to use a binary measure to distinguish dominant lead arrangers from the others (see, e.g., Ross, 2010; McCahery and Schwienbacher, 2010). The binary-based classification of the differences between lead arrangers seems consistent with the literature suggesting that reputation has a threshold. Following that literature, this paper uses a dummy variable that identifies lead arrangers in the top 3 percentile (*Top 3 Arranger*) and top 10 percentile (*Top 10 Arranger*) in terms of their market share. When a facility is arranged by multiple lead arrangers, this paper designate a loan as arranged by a dominant lead arranger if at least one of its lead arrangers is in the top tier.

3.5 *Measuring the Distance Between Lead Arrangers and Borrowers*

To measure the physical distance between a loan's lead arranger and borrower, this paper hand collects information on their geographic location. The DealScan data provide addresses of some of the borrowers. For borrowers with missing addresses, information on cities and states in which the firms are located is collected from the Securities and Exchange Commission (SEC) 10-k fillings and Bloomberg. To manage the hand collection of the lead arrangers' addresses, those lead arrangers whose headquarters are located in the geographic regions outside North America are excluded from the analysis.[4] The addresses of the remaining lead arrangers are collected from the Call Reports and the National Information Center (NIC) of the Federal Reserve System. After the cities and states in which the lead arrangers and borrowers reside are collected, the next task was to manually collect the latitude and longitude of each city. The spherical distance in kilometers, which is denoted by $Distance_{i,j}$, between lead arranger i and borrower j is calculated using the formula provided by Dass and Massa (2011):

$$Distance_{i,j} = \arccos(deg[latlon]) \times r, \tag{8}$$

where

$$\begin{aligned} deg_{latlon} = {} & \cos(lat_i) \times \cos(lon_i) \times \cos(lat_j) \times \cos(lon_j) \\ & + \cos(lat_i) \times \sin(lon_i) \times \cos(lat_j) \times \sin(lon_j) \\ & + \sin(lat_i) \times \sin(lat_j) \end{aligned} \tag{9}$$

4 Since the headquarters of most of the lead arrangers in the sample are located in the North America geographic region, the exclusion does not influence the result.

r is the Earth's radius in kilometers; *lat* and *lon* denote the latitude and longitude converted to radians from degrees by multiplying by $\pi/180$. When more than one lead arranger is involved in arranging a loan, this study selects the closest geographic distance between a lead arranger and the borrower. The distance used as an instrument is measured by the natural logarithm of one plus the spherical distance.

3.6 *Measuring Other Independent Variables*

The analysis uses an array of other independent variables to isolate the effects of factors that may influence the share retained by lead arrangers. One set of such independent variables corresponds to lead-arranger characteristics. The size of a lead arranger is measured by the natural logarithm of the book value of total assets, and it is denoted by *Arranger Size*. When information on a lead arranger's total assets is not available in the Compustat database, this study uses the information on the total assets of the lead arranger's parent company. Again, if there is no information on the total assets at the parent company level, the total assets of the ultimate parent company is used. For loan facilities that have more than one lead arranger, the total assets of the lead arranger retaining the largest share is used. When more than one lead arranger retains the largest share, this paper uses the average of their total assets.

Another set of independent variables corresponds to loan characteristics. Loan size is measured by the natural logarithm of a loan facility amount, and is denoted by $\ln(\textit{Loan Amount})$. Loan maturity is measured by the natural logarithm of the number of months from the facility start date to the facility end date and is denoted by $\ln(\textit{Loan Maturity})$. The analysis uses a categorical indicator of loan types to distinguish whether a loan facility is a revolver, a term loan, a 364-day facility, or another loan type. Another categorical indicator of loan purpose is used to identify whether a loan is used for corporate purposes, working capital, debt repayment, takeover, or another purpose.

The final set of independent variables corresponds to borrower characteristics. The size of the firm is measured by the natural logarithm of sales at close, and is denoted by *Firm Size*.[5] Limited information about a firm is measured by a dummy variable, *Opacity*, which takes the value one for firms without S&P long-term issuer ratings. Firm reputation is measured by the natural logarithm of the number of times the firm has previously borrowed in the syndicated-loan market. Firm profitability is measured by EBITDA scaled by total assets. Firm leverage is measured by the ratio of total debt, which is the sum of debt in current liability and long-term debt, to total assets. Tangibility is measured by the ratio of property, plant and equipment to total assets. The possibility that a firm may go bankrupt is measured by a dummy variable, *Financial Distress*, which takes the value one for firms with an Altman (1968) Z-Score less than or equal to 1.81. All variables used in this study are formally defined in the Appendix.

3.7 *Summary Statistics*

Table 11 summarizes the sample's descriptive statistics calculated using all observations. Since some firms appear more than once in the sample, summary statistics of the borrowing firms are calculated at a firm-year level. For the remaining variables, their summary statistics are computed at a loan-facility level. Panel A summarizes descriptive statistics of lending relationships. The data reported in this panel show that relationship lenders often head syndicated loan arrangements. As suggested by the mean of *Relation Binary*, 53% of syndicated loans are organized by lead arrangers with whom the borrowers have prior lending relationships.

The data further suggest that lead arrangers contribute a larger share to a loan. As the structure of loan syndication summarized in Panel B shows, the mean of *Retained Share* indicates that lead ar-

5 As one can note, the measure of size for the borrowers is different from that for lead arrangers. To be consistent with other studies, the present study also uses sales at close to measure the borrower's size. The result is robust to using total assets

Table 11. Summary Statistics of Syndicated Loan Facilities

This table presents summary statistics for the sample of syndicated loan facilities. The sample has 43,651 syndicated loan facilities made to U.S. nonfinancial firms, spanning the time period from 1987 through 2013. Summary statistics are calculated at a loan facility level except summary statistics of the borrowers, which are calculated at the firm-year level. All variables are defined as in the Appendix.

				Distribution				
	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max
Panel A: Lending Relationships								
Relation Binary	36,293	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Relation Number	36,293	0.36	0.40	0.00	0.00	0.20	0.75	1.00
Relation Amount	36,293	0.32	0.38	0.00	0.00	0.12	0.59	1.00
Panel B: Syndicate Structure								
Retained Share	13,443	30.01	24.04	0.00	11.67	22.00	42.86	100.00
No. of lead arrangers	43,651	1.37	0.83	1.00	1.00	1.00	2.00	21.00
Panel C: Lead arranger characteristics								
Top 3 Arranger	43,594	0.34	0.47	0.00	0.00	0.00	1.00	1.00
Top 10 Arranger	43,594	0.55	0.50	0.00	0.00	1.00	1.00	1.00
Arranger Size, $B	17,973	818.80	737.65	0.01	222.03	621.76	1,291.80	3,771.20
Small Arranger	41,824	0.45	0.50	0.00	0.00	0.00	1.00	1.00
Panel D: Loan Characteristics								
Loan Amount($M)	43,650	327.69	744.73	0.00	45.00	125.00	320.00	30,000.00
Loan Maturity	40,675	48.55	24.99	0.00	33.00	57.00	60.00	396.00
Term Loan	43,651	0.27	0.44	0.00	0.00	0.00	1.00	1.00
Revolver	43,651	0.56	0.50	0.00	0.00	1.00	1.00	1.00
364-day facility	43,651	0.09	0.28	0.00	0.00	0.00	0.00	1.00
Corporate Purpose	43,651	0.34	0.47	0.00	0.00	0.00	1.00	1.00
Working Capital	43,651	0.15	0.36	0.00	0.00	0.00	0.00	1.00
Takeover	43,651	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Debt Repayment	43,651	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Covenant	43,651	0.50	0.50	0.00	0.00	1.00	1.00	1.00
P.Covenant	43,651	0.45	0.50	0.00	0.00	0.00	1.00	1.00
Panel E: Borrower Characteristics								
Opacity	25,656	0.60	0.49	0.00	0.00	1.00	1.00	1.00
Firm Size, $B	22,068	6.83	49.69	0.00	0.35	1.11	3.86	1,843.64
Small Firm	22,068	0.50	0.50	0.00	0.00	0.00	1.00	1.00
Profitability	23,040	0.13	0.09	−0.21	0.09	0.12	0.17	0.42
Tangibility	23,095	0.35	0.25	0.00	0.15	0.30	0.54	1.00
Leverage	23,109	0.32	0.21	0.00	0.17	0.31	0.45	0.82
Financial Distress	21,306	0.34	0.47	0.00	0.00	0.00	1.00	1.00

rangers retain on average 30.01% of the loan. Inspection of the distribution of this variable also reveals that the retained share varies widely, with the values raging from 0% to 100%. While the minimum of *Retained Share* suggests that some lead arrangers syndicate out the entire loan they organize, the maximum of this variable indicates that other lead arrangers retain the full amount. This panel further demonstrates that the syndicated loan market is dominated by facilities arranged by a single lead arranger, which account for nearly 75% of the syndicated loans in the sample.

The data provide additional information that a small number of lead arrangers control loan syndication activities. As reported in Panel C, which summarizes the lead arrangers' characteristics, the mean of *Top 3 Arranger* indicates that 34% of syndicated loans are arranged by lead arrangers whose syndicated market share lies in the top 3 percentile. This finding is consistent with the result of previous studies that less than a dozen lead arrangers are responsible for more than half of loan syndication (Sufi, 2007; Do and Vu, 2010; McCahery and Schwienbacher, 2010). One plausible explanation for the greater involvement of a handful of arrangers in loan syndication activities would be that top arrangers have a well-established and extensive networks of lenders (Godlewski et al., 2012; Cai et al., 2014). This obviously enables them to easily syndicate out the loans they originate.

Syndicated loan facilities are characterized in Panel D. The average facility amount is 327.69 million dollars with a standard deviation of 744.73 million dollars. Loan facilities have an average maturity of 48.55 months, and a median maturity of 57 months. In terms of loan types, the line of credit (revolver) is the most common, accounting for 56% of the facilities in the sample. The next largest loan type, which accounts for nearly 27% of the syndicated facilities, is the term loan. Finally, syndicated loans are typically used to fund corporate purposes, which accounts for 34% of the loans in the sample. Other major purposes for which syndicated facilities are used are to working capital (15%), debt repayment (16%) and takeover (11%).

Panel E reports annual financial summary statistics of the borrowing firms. On average, borrowing firms have 6.83 billion dollars in sales at close. In terms of long-term issuer credit ratings, 40% of firms in the sample have S&P credit ratings, of which 11% have speculative-grade ratings. Firm profitability (EBITDA/Total assets) is Winsorized at the 1st and the 99th percentiles to eliminate the influence of extreme outliers. Firm leverage is Winsorized at the 95th percentile as Winsorization at the 99th percentile does not remove the extreme values. After Winsorization, firms have an average profitability of 13% and an average leverage is 38%. The average tangible-assets ratio is 35%. Nearly 34% of firms in the sample are financially distressed in the sense that they have Altman (1968) Z-Score less than or equal to 1.81.

3.8 *Preliminary Analysis*

This section deals with the preliminary analysis of the empirical association between the retained share and the lead arranger's lending relationships with the borrower. The preliminary analysis is conducted by way of univariate tests of the differences in the share retained by relationship and nonrelationship lead arrangers. To carry out a univariate test, syndicated loan facilities are partitioned into two groups on the basis of whether a facility is originated by a relationship lead arranger. Accordingly, using a binary measure of a lending relationship, a loan facility is designated as a relationship loan when *Relation Binary* $= 1$, and as a nonrelationship loan facility when *Relation Binary* $= 0$.

The univariate-based analysis of the means of syndicate structure, lead arrangers, loan facilities, and borrower characteristics is reported in Table 12. In the first column of this table, the means of the variables associated with loans syndicated by relationship lead arrangers are presented. The second column reports the means of the variables corresponding to facilities syndicated by nonrelationship lend arrangers. The differences of these means are displayed in the last column. The t test of the statistical significance of the differences in means is indicated by asterisk, where three asterisks indicates significant at the 1% level, two at the 5% level and one at the 10% level.

The univariate analysis suggests that the share retained by lead arrangers with whom the borrowing firms have lending relationships significantly differs from the share held by nonrelationship lead arrangers. As the mean of *Retained Share* shows, relationship lead ar-

Table 12. Univariate Analysis of Variables by the Existence of Lending Relationships

This table presents a univariate analysis of the means of the variables used in this study. Columns (1) and (2) present the means and standard deviations (SD) of the variables for syndicated loans arranged by relationship lead arrangers. Columns (3) and (4) report the means and standard deviations of the variables for loans syndicated by nonrelationship lead arrangers. Column (5) displays the difference in means of the variables presented in Columns (1) and (3). Column (6) presents the standard deviation of the difference in means. All variables are defined as in the Appendix. The *t* test of the statistical significance of the differences in means is indicated by asterisk, where ***, **, and * indicate significance at the 1% level, the 5% level and the 10% level, respectively.

	Relationship Loans		Nonrelationship Loans		Difference	
	[Mean]	[SD]	[Mean]	[SD]	[Mean]	[SD]
	(1)	(2)	(3)	(4)	$(5 = 1 - 3)$	(6)
Retained Share	25.201	(21.530)	32.517	(24.965)	-7.316^{***}	(0.448)
Top 3 Arranger	0.445	(0.497)	0.268	(0.443)	0.177^{***}	(0.005)
Top 10 Arranger	0.659	(0.474)	0.458	(0.498)	0.202^{***}	(0.005)
Arranger total assets	939.134	(780.842)	758.003	(683.241)	181.131^{***}	(12.026)
Small Arranger	0.407	(0.491)	0.418	(0.493)	-0.011^{*}	(0.005)
Opacity	0.488	(0.500)	0.607	(0.488)	-0.119^{***}	(0.005)
Total no. prev. borrow	4.946	(3.610)	3.331	(3.027)	1.615^{***}	(0.035)
Sales at close	9.199	(57.157)	6.353	(60.865)	2.846^{***}	(0.663)
Small Firm	0.400	(0.490)	0.554	(0.497)	-0.154^{***}	(0.006)
Profitability	0.132	(0.080)	0.128	(0.090)	0.003^{***}	(0.001)
Tangibility	0.365	(0.249)	0.344	(0.241)	0.021^{***}	(0.003)
Leverage	0.362	(0.210)	0.348	(0.228)	0.015^{***}	(0.002)
Financial Distress	0.382	(0.486)	0.362	(0.481)	0.020^{***}	(0.006)
Loan Amount($M)	425.957	(848.422)	268.202	(696.285)	157.756^{***}	(8.220)
Loan Maturity	47.488	(24.676)	49.049	(24.713)	-1.562^{***}	(0.269)
Term Loan	0.260	(0.439)	0.283	(0.450)	-0.023^{***}	(0.005)
Revolver	0.549	(0.498)	0.560	(0.496)	-0.010	(0.005)
364-day facility	0.114	(0.318)	0.068	(0.251)	0.047^{***}	(0.003)
Corporate Purpose	0.372	(0.483)	0.319	(0.466)	0.052^{***}	(0.005)
Working Capital	0.140	(0.347)	0.157	(0.364)	-0.017^{***}	(0.004)
Takeover	0.099	(0.298)	0.109	(0.312)	-0.010^{**}	(0.003)
Debt Repayment	0.163	(0.369)	0.161	(0.367)	0.002	(0.004)
Covenant	0.504	(0.500)	0.536	(0.499)	-0.032^{***}	(0.005)
P.Covenant	0.445	(0.497)	0.483	(0.500)	-0.038^{***}	(0.005)

rangers hold on average 25.20% of the loan. For the nonrelationship lead arrangers, the retained share is increased to 32.52%. The difference in the retained share is -7.32%, and is statistically significant at the 1% level. This mean difference indicates that the retained share is significantly smaller on a loan syndicated by lead arrangers that have lending relationships with the borrower vis-à-vis the retained share in a loan syndicated by nonrelationship lead arrangers. The apparently inverse empirical association between lending relationships and the retained share may provide preliminary evidence that establishing lending relationships with firms enables lead arrangers to syndicate out more of the loans issued to the firms.

However, caution should be exercised at this stage with the above conclusion drawn from the univariate test for the simple reason that the mean comparison also shows a significant difference between relationship and nonrelationship loans in many other respects. As can be seen from the result reported in Table 12, potential explanatory variables of the retained share differ considerably between syndicates headed by relationship and nonrelationship lead arrangers. It is thus plausible that the result from the unconditional mean comparison may reflect the effects of other determinants of the retained share. As such, the observed reduction in the retained share may not be entirely attributable to lending relationships. That is, significant differences in important characteristics between syndicates headed by relationship and nonrelationship lead arrangers are likely to influence the difference in the retained share.

One important difference is related to lead-arranger characteristics. For example, the mean of *Top 3 Arranger* shows that 45% of relationship loans are arranged by lead arrangers whose reputation lies in the top 3 percentile and only 27% for the nonrelationship loans. The difference is statistically significant at the 1% level. Again, the univariate test shows that relationship loans tend to be arranged by large lead arrangers compared to nonrelationship loans. The prior literature has established that lead arrangers' reputation and size influence loan syndication activities. It therefore follows that both of these patterns could influence the differences in the retained share obtained from the unconditional mean analysis.

Another important difference is associated with borrower characteristics. As the univariate analysis shows, firms obtaining loans from relationship lead arrangers are not representative of firms getting loans from nonrelationship lead arrangers. Table 12, for example, shows that while 49% of relationship loans are borrowed by firms that do not have S&P credit ratings, the percentage is 61% for the nonrelationship loans. The difference is statistically different from zero at the 1% level. This appears to indicate that relationship lead arrangers syndicate loans to relatively more transparent firms. Furthermore, loans originated by relationship lead arrangers are made to relatively larger borrowers compared to loans syndicated by nonrelationship lead arrangers. Firms borrowing from relationship lead arrangers are more profitable than firms borrowing from nonrelationship lead arrangers. Research has shown that borrowers' informational opacity and size are important determinants of the retained share. The omission of these variables plausibly affect the observed difference in the retained share.

The other key difference is related to loan characteristics. One can observe that the average amount of relationship loans is 425.96 million dollars, which is almost twice the size of the average amount of a nonrelationship loan, 268.2 million dollars. Apparently, loans syndicated by relationship lead arrangers are considerably larger than those arranged by nonrelationship lead arrangers. Failing to control for such loan terms may also affect the differences in the retained share. To adjust for the potential effects stemming from these factors, the next section controls for the above variables in the regression analysis.

4 RELATIONSHIP LENDING AND RETAINED SHARE: EMPIRICAL RESULTS

4.1 *Baseline Specification*

This section lays the empirical groundwork for the regression analysis of the empirical association between lending relationships and the share retained by lead arrangers in syndicated loans. The analysis is conducted using a variant of a regression model that accounts for factors that could influence the retained share. The baseline regression model is specified as

$$Retained\ Share_{i,j,l} = \alpha + \beta Relationship_{i,j,l} + \gamma X_{i,t-1} + \eta X_{j,t-1} + \psi X_l + \mu + \epsilon_{i,j,l} \quad (10)$$

The dependent variable, *Retained Share*$_{i,j,l}$, is the percentage held by a lead arranger i (the retained share) on a loan facility l made to a borrower j. The key independent variable of interest, denoted by *Relationship*$_{i,j,l}$, measures previous lending relationships between the loan's lead arranger and borrower. Given the two competing views discussed in the paper, the coefficient of interest, β, measures the net effect of relationships on the lead arranger's retained share. A negative value suggests that the credible-commitment-to-monitoring view of a lead arranger's lending relationships with firms outweighs the information-exploitation view. This regression model also includes several other independent variables, which, for the sake of clarity, are presented as lead-arranger, borrower and loan controls.

Lead-arranger Controls: The variable $X_{i,t-1}$ stands for lead-arranger characteristics. It is argued in Section 2 that the lead arranger's reputation helps mitigate agency conflicts, and that this would promote retaining a smaller fraction of syndicate loans. Also, large lead arrangers are presumed to have the necessary skills and resources to conduct adequate screening and monitoring, so this would allow them to finance a smaller portion of the loan. This study controls for such possibilities using *Top 3 Arranger* and *Arranger Size*.

Borrowing-firm Controls: The variable $X_{j,t-1}$ captures borrower characteristics. As discussed in Section 2, a limited availability of the borrower's information exacerbates agency problems, considerably increasing the fraction of the loan financed by the lead arranger. Following previous studies, the current study controls for this notion with an indicator variable *Opacity*. The reputation and the size of the borrowing firms have also been identifies as major factors that facilitate syndication activities (Sufi, 2007; Cai, 2010). This study thus controls for these potential factors using *Firm Reputation* and *Firm Size*. The remaining firm-specific controls include firm profitability, tangibility, leverage, and financial distress.

Syndicated-loan Controls: The variable X_l represents a vector of loan characteristics. The regression equation includes loan-facility size, denoted by ln(*Loan Amount*), and loan maturity, ln(*Loan Maturity*). Additionally, this study uses an array of dummy variables to control for the type and the purpose of the loan. The loan-type dummies account for whether the syndicated loan is a revolver (lines of credit), a term loan or a 364-Day facility. The loan-purpose dummies account for whether the loan is for working capital, corporate purposes, debt repayment or takeover.

Fixed-effect Controls: In the above regression specification, μ controls for the borrower's industry fixed effects (Industry dummy) using a one-digit Standard Industrial Classification (SIC). It also controls for the loan-facility-start year fixed effects (Year dummy). There might also exist persistent firm-specific attributes that introduce correlations across observations within firms. A standard approach to control for this possibility is to use a firm fixed-effects dummy or clustering by firm. Petersen (2009) and Gow et al. (2010), however, argue that the conventional fixed-effect dummy, which requires the assumption of a constant effect, may not fully remove dependences between observations. That is, when there exist time-varying firm-specific effects, the fixed-effect approach continues to produce biased standard errors. They suggest clustering standard errors by firms. Accordingly, this analysis accounts for any potential correlations across observations by running a regression model clustering standard errors at the firm level.

4.2 *The Effect of Relationships and on the Retained Share*

This paper has raised two competing views about the effect of relationships on the retained share. The empirical analysis in this section indicates that the monitoring view outweighs the exploitation view in the syndicated loan market, and this result is depicted in Table 13. As can be seen from the result reported in Column (1), the binary measure of a lending relationship (*Relation Binary*) is negatively and significantly associated with the retained share. This result shows that lead arrangers who were previously involved in lending relationships with the borrower retain 2.43% less of the loan they arrange for the borrower in the subsequent years. The reported reduction is statistically significant at the 1% level. This result is in line with the view that relationships facilitate information production, which enhances monitoring and mitigates the agency problems to which participants are exposed. As a result, relationship lead arrangers are not required to structure syndicates such that they retain a larger share.

Beyond the statistical significance, the reported reduction in the retained share is also economically nonnegligible. To demonstrate this assertion, consider lead arrangers holding the sample average share of 30.01%. For these lead arrangers, the existence of previous lending relationships will lead to an 8.1% reduction of the retained share (-2.43/30.01 $\times$ 100). This means that, in terms of the retained amount, lead arrangers organizing a syndicated loan with the sample average amount of 327.69 million dollars for borrowers with whom they have prior lending relationships will be able to contribute 7.97 million dollars (327.69 $\times$ 30.01% $\times$ 8.1%) less than they would otherwise have to contribute if they had not established a lending relationship with the borrower.

The above analysis is repeated in column (2) by running a model in which the retained share is regressed on the proportion of the number of times that the lead arranger and the borrower previously interacted. The result shows that the previously observed pattern continues to hold mainly in the sense that the continuous measure of relationships (*Relation Number*) is negatively and statistically significantly related to the retained share. It thus appears that the greater the intensity of lending relationship involvements with borrowers, the more likely that loans are syndicated out. One may explain this result along the lines that repeated interactions over time (i.e., long-lasting relationships) could encourage borrowers to divulge more proprietary information. One could also envision the quality of information generated to be a function of repeated interactions, which permits the accumulation and utilization of the proprietary information. This signals the lead arranger's monitoring-cost advantage to participants.

Table 13. The Effect of Relationships and on the Retained Share

This table presents coefficient estimates from regressing the percentage of a syndicated loan retained by a lead arranger (*Retained Share*) on the measures of a lending relationship between the lead arranger and the borrower. *Relation Binary* indicates whether a prior lending relationship exists between the lead arranger and the borrower of a syndicated loan. *Relation Number* captures the proportion of the previous lending relationships in terms of the number of interactions. *Relation Amount* accounts for the proportion of the previous lending relationships in terms of the amount of interactions. All other variables are defined as in the Appendix. Column (1) reports results when *Relation Binary* is used as the main variable of interest. Column (2) runs the analysis using *Relation Number* as a measure for relationship lending. Column [3] estimates the model in which relationship lending is measured by *Relation Amount*. Columns (4)–(6) repeat the same exercise replacing *Top 3 Arranger* with *Top 10 Arranger*. Standard errors are heteroskedasticity robust and clustered at the borrower level. The t-test of significance is represented as: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Retained Share					
	(1)	(2)	(3)	(4)	(5)	(6)
Relation Binary	−2.429***			−2.141***		
	(0.52)			(0.52)		
Relation Number		−2.268***			−1.919***	
		(0.62)			(0.61)	
Relation Amount			−2.009***			−1.689***
			(0.65)			(0.65)
Top 3 Arranger	−3.626***	−3.705***	−3.742***			
	(0.54)	(0.54)	(0.54)			
Top 10 Arranger				−5.471***	−5.556***	−5.604***
				(0.65)	(0.65)	(0.65)
Arranger Size	−1.254***	−1.252***	−1.249***	−0.579	−0.567	−0.558
	(0.39)	(0.39)	(0.39)	(0.41)	(0.41)	(0.41)
Opacity	1.577*	1.594*	1.675**	1.460*	1.475*	1.542*
	(0.82)	(0.82)	(0.82)	(0.82)	(0.82)	(0.82)
Firm Reputation	−0.524	−0.917**	−0.881**	−0.573	−0.917**	−0.886**
	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)
Firm Size	−1.745***	−1.771***	−1.778***	−1.714***	−1.737***	−1.742***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.26)	(0.26)
Profitability	−1.386	−1.005	−1.134	−0.941	−0.608	−0.713
	(4.16)	(4.16)	(4.17)	(4.10)	(4.10)	(4.10)
Tangibility	−2.054	−2.167	−2.111	−2.169	−2.267	−2.221
	(1.41)	(1.41)	(1.41)	(1.41)	(1.41)	(1.41)
Leverage	−4.928***	−4.788**	−4.846**	−4.735**	−4.609**	−4.656**
	(1.89)	(1.89)	(1.89)	(1.88)	(1.87)	(1.87)
Financial Distress	1.339	1.375	1.334	1.488*	1.520*	1.487*
	(0.86)	(0.86)	(0.86)	(0.86)	(0.86)	(0.86)
ln(*Loan Amount*)	−6.807***	−6.811***	−6.819***	−6.658***	−6.662***	−6.667***
	(0.35)	(0.35)	(0.35)	(0.34)	(0.34)	(0.34)
ln(*Loan Maturity*)	−5.034***	−5.011***	−5.007***	−4.969***	−4.948***	−4.944***
	(0.56)	(0.57)	(0.57)	(0.56)	(0.56)	(0.56)
Loan-type dummies	YES	YES	YES	YES	YES	YES
Loan-purpose dummies	YES	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
R^2	0.413	0.412	0.412	0.419	0.418	0.418
N	7,659	7,659	7,659	7,659	7,659	7,659

It could also be argued that repeated interactions provide lead arrangers with punishment mechanisms that instill an interest in firms to develop self-disciplining behavior. The theoretical result in the finance literature shows that credible penalties make defaults less of a problem (see, e.g., Allen, 1981). The idea is that a borrower's current misbehavior has considerable consequences for its access to credit in the future from the same lenders; bad behavior might not go without being penalized. One form of penalty may be charging a higher interest rate. That is, currently poorly performing borrowers face higher interest rates in future loans they obtain from the same lenders (Stiglitz and Weiss, 1983). The other form of penalty may be a termination threat (Stiglitz and Weiss, 1983; Bolton and Scharfstein, 1990). Lenders may terminate a future loan contract to firms that perform poorly during the current period. Thus, repeated interactions make it possible for lead arrangers to impute premiums in the form of punishments so that borrowers that value more future relationships—i.e., firms that assess the benefit from a current cheating to be less than the cost of losing future relationships—would self-restrain. Thus, these punishment mechanisms solve one layer of agency conflicts in loan syndication, which facilitates lead arrangers' syndication activities.

The additional analysis is continued in the third column by regressing the retained share on the proportion of the amount of syndicated loans that the lead arranger has organized for the firm. The reported result shows that *Relation Amount* is also negatively and statistically significantly related to the percentage retained. This amount-based measure also provides further evidence of how lending relationships influence syndication activities. Specifically, the inversely estimated association between the amount-based measure of lending relationships and the retained share may suggest that lenders arranging loans for firms for whom they have previously provided large amounts of loans retain a smaller share in the current loan. This result follows perhaps because borrowers tend to disclose more proprietary information or place more value on their relationships with lead arrangers on whom they heavily depend in terms of loan size.

In the three remaining columns of Table 13, this paper reruns the analysis in the first three columns with a different measure of lead arrangers' reputation: substituting *Top 3 Arranger* with *Top 10 Arranger*. As one would expect, all the coefficients of the measures of lending relationships are negatively and statistically significantly estimated. Thus, except for a small reduction in the estimated magnitudes, the conclusion drawn above remains unchanged.

The control variables have the expected signs, and most of their coefficients are also statistically significant. For example, more reputable and larger lead arrangers retain smaller shares. Lead arrangers organizing syndicated loans for informationally opaque firms retain more of the loans. But when the borrowing firm is reputable, lead arrangers retain less of the loan. In line with the argument based on agency theory that lenders use loan terms—specifically, smaller size and shorter maturities—to control firms that suffer from greater agency problems, the lead arrangers' retained share decreases with loan size and maturity.

4.3 *Endogeneity Problems*

A potential concern with the result presented above is endogenous relationship formation. It is plausible that the decision to borrow from a previous relationship lead arranger or to lend to a previous relationship borrower may not be made at random, but endogenously chosen. If uncontrolled observable and unobservable characteristics are associated with the lead arranger's choice and also determine the share retained by the lead arranger, the OLS regression may confound the effect of lending relationships with the effect of these uncontrolled covariates. Thus, a robustness check needs to be performed to determine whether the potential nonrandomness of the lead arranger–firm matching drives the result and invalidates the inference about the impact of lending relationships on the retained share drawn from the OLS analysis. This is the objective of the next sections.

4.3.1 *Mahalanobis and Propensity Score Matching*

One alternative econometric method often used in observational studies that can help this study analyze situations where financing decisions are made endogenously is the matching method (Heckman et al., 1997; Imbens and Wooldridge, 2009). The matching method addresses the endogeneity concern by identifying a set of control groups (i.e., loan facilities provided by nonrelationship lead arrangers in this study) that best match the treated group (i.e., loan facilities provided by relationship lead arrangers in this paper). After identifying the closest comparison group, the matching method computes the differences in the retained share (i.e., the outcome variable) between the matched relationship and nonrelationship loans. Since the treated and control groups are similar, any difference in the retained share is presumed to be the effect of the variable of interest, the lending relationship in this case.

The current study uses several different methods proposed by the literature to identify a control group. One such method is covariate-based matching. The basic idea of this method is to use all observable covariates jointly to select a set of nonrelationship loans (the control group) whose covariate values are similar to those of the relationship loans (the treated group). However, comparison on multiple dimensions (i.e., the use of several covariates) may lead to poor distributional overlap and introduce bias. To avoid such potential bias, the literature suggests using Mahalanobis matching (Cochran and Rubin, 1973; Rubin, 1980). In this matching framework, control groups are chosen on the basis of their Mahalanobis distance from the treated group, given as

$$MD_{l_{r,i}l_{nr,i}} = (X_{l_{r,i}} - X_{l_{nr,j}})' \sum^{-1} (X_{l_{r,i}} - X_{l_{nr,j}}) \tag{11}$$

where $\mathrm{MD}_{l_{r,i}l_{nr,i}}$ is the Mahalanobis distance between a relationship loan $l_{r,j}$ and a nonrelationship loan $l_{nr,j}$. $X_{l_{r,i}}$ and $X_{l_{nr,j}}$ are the vectors of observed covariates corresponding to relationship and nonrelationship loans, respectively. $\sum$ is the sample variance–covariance matrix. For each relationship loan, this study selects a control group of nonrelationship loans that minimizes the Mahalanobis distance matrix. The literature, however, has shown that the Mahalanobis-distance-based matching is susceptible to bias with a large number of covariates (Gu and Rosenbaum, 1993).

To test the sensitivity of the results, this study uses an alternative method to select a control group: propensity-score matching (PSM; Rosenbaum and Rubin, 1983; Abadie and Imbens, 2006, 2008). This approach mitigates the above bias problem by matching on a function of the covariates instead of on the covariates themselves. That is, it solves the problem by reducing comparability to a single dimension (the propensity score). A unidimensional comparison (i.e., a scalar function of the covariates) offers attractive properties in that the scalar facilitates matching and eliminates the potential curse of the dimensionality problem associated with covariate-based matching. PSM chooses a control group based on the probability of being included in the treated group. In this study, this means that each relationship loan is matched to a set of nonrelationship loans that have similar propensity for being syndicated by relationship lead arrangers. To apply the PSM, this study first runs a regression model:

$$\Pr(\textit{Relation Binary}_{i,j,l} = 1) = \alpha_0 + \alpha_1 X_{i,t-1} + \alpha_2 X_{j,t-1} + \eta\alpha_3 X_l + \mu_i, \quad (12)$$

where $\Pr(\cdot)$ denotes a probit model used to estimate the probability that a facility is syndicated by a relationship lead arranger. The central issue in the PSM is the choice of the covariates used to estimate the propensity scores. Several studies suggest including variables that affect both the outcome and treatment variables in the estimation of the propensity scores (see, e.g., Rubin and Thomas, 1996; Heckman et al., 1998; Marco and Kopeinig, 2008). Accordingly, the above model uses lead arranger ($X_{i,t-1}$), borrower ($X_{j,t-1}$) and loan (X_l) characteristics that are presumed to have potential to affect the retained share and the probability of the loan being a relationship loan. The model also controls for the purpose of the loan, the type of the loan, the one-digit borrower industry and the year fixed effects.

There are several standard estimators for implementing this matching technique. This study focuses on the two commonly used in empirical studies. One widely used estimator is *nearest neighbor* matching (Cochran and Rubin, 1973; Rubin, 1973). For each treated unit, this estimator finds the nearest neighbor in the control group to generate a matched pair. In this study, this estimator calculates the difference in the retained share between a relationship loan and n nonrelationship loans for which the Mahalanobis distance matrix is at its minimal, or that have the closest propensity score. To get correct standard errors for the nearest-neighbor estimator, this study uses the Abadie and Imbens (2006) variance estimator.

The other commonly used estimator is *Kernel* matching (Heckman et al., 1997, 1998). In this study, the kernel calculates the difference in the retained share between a relationship loan and the weighted average of the retained share in nonrelationship loans. The weights are assigned in that those nonrelationship loans with the closest propensity scores to the given relationship loan receive a higher weight. The *Epanechnikov* kernel uses only nonrelationship loans whose propensity scores lie within a given bandwidth while the *Gaussian* kernel uses all nonrelationship loans to calculate the weighted average. Correct standard errors for the kernel estimators are obtained by using bootstrapping with 100 replications.[6] Furthermore, for the Epanechnikov estimator, this study uses a propensity-score bandwidth of $h = 0.01$.

The matching-analysis results show that relationship loans do have lower retained share than similar nonrelationship loans (Table 14). The analysis first undertakes *one-to-one* matching based on the Mahalanobis distance metric. As can be noted from Column (3) (the difference in the retained share), the one-to-one estimator shows that the average treatment effect on the treatment loans (*ATT*) is -1.176. One can note from Table 14 that with increasing Mahalanobis distance (i.e., using more nonrelationship loans in the control group), the retained share in relationship loans continued to be consistently lower than the retained share in nonrelationship loans.

6 This study uses the STATA code PSMATCH2 (Leuven and Sianesi, 2003, version 4.0.11, 22 October 2014) to implement the PSM technique.

Table 14. Mahalanobis and Propensity Score Matching

This table reports results from the Mahalanobis and PSM techniques. The nearest neighbor estimator calculates the difference in the retained share between each relationship loan and n nonrelationship loans that have the closest Mahalanobis distance or with the nearest propensity scores. The Epanechnikov estimator uses nonrelationship loans with the propensity scores within the bandwidth $h = 0.01$. The Gaussian estimator uses all nonrelationship loans to calculate the difference in the retained share. *ATT* denotes the average treatment on the treated loan. The t-test of significance is represented as: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Treated obs.	Untreated obs.	*ATT*
	(1)	(2)	(3)
Panel A: Mahalanobis distance matching			
One-to-one	4,521	3,139	-1.176^{***}
			(.45)
Nearest neighbor	4,521	3,139	-1.812^{***}
($n = 10$)			(.40)
Nearest neighbor	4,521	3,139	-2.713^{***}
($n = 50$)			(.42)
Panel B: Propensity score matching			
One-to-one	4,504	3,139	-1.784^{***}
			(.67)
Nearest neighbor	4,504	3,139	-2.001^{***}
($n = 10$)			(.53)
Nearest neighbor	4,504	3,139	-2.075^{***}
($n = 50$)			(.51)
Epanechnikov	4,469	3,139	-2.059^{***}
			(.52)
Gaussian	4,504	3,139	-2.096^{***}
			(.51)

The retained-share difference is also supported when matching is based on the propensity score. For example, the one-to-one estimator shows that the *ATT* is -1.784. Relaxing the restriction on the number of nonrelationship loans used as a control group does not affect the result. For example, the nearest neighbor estimator reports the *ATT* of -2.001 for $n = 10$ and -2.075 for $n = 50$. Using the Epanechnikov kernel estimator—excluding nonrelationship loans for which the difference in propensity score between the matched pair exceeds the given propensity score bandwidth—the matching analysis yields an *ATT* of -2.059. Extending the facilities included in the control group to all nonrelationship loans, the Gaussian kernel estimator generates an *ATT* of -2.096. Thus, it appears from this analysis that after controlling for selection on observables, lending relationships continue to have the retained-share-reducing effect.

4.3.2 *Binary Endogenous Treatment Models*

While the matching method employed in the previous section controls for a bias stemming from selection on observable factors, the endogeneity concern may still exist perhaps because the financing decision may be based on unobservable factors. An alternative econometric method that can help to control for bias stemming from selection on unobservable (and observable) factors is the binary treatment model (Heckman, 1979; Maddala, 1983; Wooldridge, 2002). The basic idea behind this method involves estimating a system of equations in which the outcome variable equation (the retained-share equation) is augmented with an additional binary endogenous treatment-variable equation (a lending-relationship-formation equation in the current study). The specification of such an endogenous-regression framework is given by the following system of equations.

$$Retained\ Share_{i,j,l} = \beta_0 + \beta_1 Relation\ Binary_{i,j,l} + Z_1^{'}\delta + \epsilon_i \qquad (13a)$$

$$Relation\ Binary*_{i,j,l} = \alpha_0 + Z^{'}\gamma + u_i \qquad (13b)$$

The estimation technique employed with this system of equations solves the endogeneity problem associated with the arranger–borrower relationship formation by allowing the residuals in the retained-share equation (13a) and the lending-relationships equation (13b) to be correlated. That is, $\text{cov}(\varepsilon_i, u_i) = \rho \neq 0$. The relationship equation is implemented as a probit model, where the dependent variable ($Relation\ Binary^*_{i,j,l}$) is a dummy that identifies whether the loan is syndicated by a relationship lead arranger. The vector $Z = (Z_1, Z_2)$ in equations (13a) and (13b) stands for observable factors that influence a lead arranger's choice. This vector includes variables (Z_1) that may determine the lead arranger's retained share and may also affect lead-arranger–borrower matching. This vector also includes a variable (Z_2) that affects lending-relationship formation, but does not affect the lead arrangers' retained share. This variable serves as an exclusion restriction for better identification purposes.

This study uses the geographic distance measured in kilometers between the lead arranger and the borrower of a loan (Section 3) as the instrument (Z_2). The choice of this variable is motivated by the standard argument in the relationship literature that a relationship-based lending technology requires the collection of a borrower's proprietary information. As noted by Petersen and Rajan (2002) and Dass and Massa (2011), geographic proximity considerably reduces the costs associated with the collection and processing of the borrower's soft information. One can thus expect geographic proximity to increase the likelihood of forming a lending relationship—i.e., affecting the lead-arranger–borrower matching. Geographic distance is, however, unlikely to directly affect the share retained by lead arrangers. This argument rationalizes the use of geographic distance as a preferred instrumenting technique in the empirical literature (see, e.g., Bharath et al., 2011; Aslan, 2015).

The binary measure, $Relation\ Binary_{i,j,l}$, in the retained share equation (13a) is modeled as an outcome of an unobserved latent variable, $Relation\ Binary^*_{i,j,l}$. Since whether a loan is syndicated by a relationship or nonrelationship lead arranger is observable, the observed binary relationship outcome variable is modeled as

$$Relation\ Binary_{i,j,l} = \begin{cases} 1, & Relation\ Binary^*_{i,j,l} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

The literature offers different methods by which the system of equations given above is estimated. One such method is called *Probit-2SLS*. This method requires applying a probit model to a relationship formation and then calculating the predicted probability of a lead arranger choice, which is later used as an instrument for a relationship formation to get a new fitted value. Finally, this method requires regressing the retained share on a new predicted probability of relationship formation. The other method is called *Probit-OLS*, where a probit model is applied to a relationship formation and then the predicted probability is calculated. In the second stage, the procedure requires running an OLS regression of the retained share on the predicted probability. The third method is called *Heckit*, a Heckman two-step selection model. All these models are estimated using a new STATA command for estimating binary endogenous treatment models called *ivtreatreg* (Cerulli, 2014).

Table 15 presents the results from the estimation of the binary endogenous treatment models. Estimates from the first stage, in which a probit model of a lending-relationship formation is estimated, are reported in Column (1). Interestingly, the estimated coefficient of the geographic distance is negative and also statistically significant at the 1% level. This result conforms with the prediction from the theoretical literature and the evidence presented in prior studies that firms in closer proximity to lenders have a greater likelihood of forming a lending relationship. The current result presents the flip side of this argument: A greater the distance reduces the chances of forming lending relationships. The analysis also shows that while reputable lead arrangers are more likely to form lending relationships, larger lead arrangers are less likely to engage in lending relationships. Additionally, while firms that are larger and more reputable are more likely to borrow from relationship lead arrangers, firms with greater leverage are less likely to be involved in relationships.

The binary endogenous treatment model estimated by Probit-2SLS in Column (2) shows that the coefficient of lending relationship is -12.93, and that it is distinct from zero at the 5% level. The third column presents the effect of lending relationship on the retained share as estimated by Probit-OLS. The estimated coefficient is -14.74 and it is significant at the 5% level. The fourth column provides a two-stage Heckman estimate. The reported coefficient of lending relationship is -14.35, which is significantly different from zero at the 5% level. These results suggest that, even after controlling for endogeneity, establishing lending relationship is associated with a significant reduction in the retained share. However, the estimation of the binary endogenous treatment models produces relationship coefficients with larger magnitude in comparison to the OLS estimates. As can be seen, these coefficients are approximately a factor of six larger.[7] This large increase might be due to the predicted relationship formation

7 Other studies have also found a larger increase in coefficient estimates. For example, Bharath et al. (2011) estimate the impact of relationships on loan spreads using IV

Table 15. Estimation of Binary Endogenous Treatment Models

This table presents the results of the effect of lending relationships on the retained share obtained from binary endogenous treatment models. Column (1) reports results from the probit first stage of relationship formation. Column (2) estimates the retained share with Probit-2SLS. Column (3) runs the retained share using the Probit-OLS estimation, and column (4) reports result from the second-stage Heckit. *Distance* is the spherical distance in kilometers between the lead arranger's and borrower's headquarters. *Relation Binary* identifies whether a loan is syndicated by a relationship lead arranger. All other variables are defined as in the Appendix. Number of observations in parenthesis is for the first-stage Heckit model. Standard errors are heteroskedasticity robust and clustered at the borrower level. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Relationship formation	*Retained Share*		
	First stage	Probit-2SLS	Probit-OLS	Heckit
	(1)	(2)	(3)	(4)
$\log(1+Distance)$	-0.036^{***}			
	(0.01)			
Relation Binary		-12.934^{**}	-14.737^{**}	-14.348^{**}
		(6.28)	(6.83)	(6.27)
Top 3 Arranger	0.351^{***}	-2.141^{**}	-1.914^{**}	-1.967^{**}
	(0.04)	(0.87)	(0.92)	(0.92)
Arranger Size	-0.058^{***}	-1.612^{***}	-1.647^{***}	-1.646^{***}
	(0.02)	(0.35)	(0.35)	(0.31)
Opacity	-0.053	1.160^{*}	1.109^{*}	1.131^{*}
	(0.04)	(0.65)	(0.63)	(0.63)
Firm Reputation	0.375^{***}	1.007	1.245	1.196
	(0.02)	(0.87)	(0.93)	(0.90)
Firm Size	0.038^{***}	-1.479^{***}	-1.453^{***}	-1.462^{***}
	(0.01)	(0.22)	(0.22)	(0.21)
Profitability	-0.182	-0.758	-0.782	-0.823
	(0.22)	(3.37)	(3.31)	(3.07)
Tangibility	0.122	-1.661	-1.612	-1.618
	(0.08)	(1.16)	(1.13)	(1.18)
Leverage	-0.169^{*}	-5.575^{***}	-5.650^{***}	-5.662^{***}
	(0.10)	(1.59)	(1.53)	(1.44)
Financial Distress	-0.012	1.576^{**}	1.554^{**}	1.575^{**}
	(0.05)	(0.69)	(0.67)	(0.67)
$\ln(Loan\ Amount)$	0.023	-6.846^{***}	-6.838^{***}	-6.833^{***}
	(0.02)	(0.32)	(0.31)	(0.25)
$\ln(Loan\ Maturity)$	-0.023	-5.045^{***}	-5.047^{***}	-5.057^{***}
	(0.03)	(0.53)	(0.52)	(0.42)
Loan-type dummies	YES	YES	YES	YES
Loan-purpose dummies	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Lambda				7.312^{*}
				(3.82)
McFadden's pseudo R^2	0.084			
R^2			0.760	
N	6,982(6,983)	6,982	6,982	6,983

not being a very good fit for *Relation Binary*, as is evident from low McFadden's pseudo R^2.[8] Since OLS yields conservative results, it is used through the remaining sections of this paper.

4.4 *Variation by Lead-Arranger Reputation and Size*

The theoretical discussion presented in Section 2 maintained that the share retained by more reputable lead arrangers is less affected by lending relationships than that retained by less reputable lead arrangers. To investigate this theoretical speculation, the measures of lending relationships are allowed to interact with the lead arrangers' reputation in the baseline regression model. The results of the analysis of the variation of the effect of lending relationships on the retained share by the lead arranger's reputation reported in Table 16 support the above claim.

As the present finding shows, the reduction in the retained share is largely confined to syndicated arrangements with less reputable lead arrangers. This finding is evident from the result (Column (1)) using the interaction term between the binary measure of lending relationships and the top-tier dummy, *Relation Binary* $\times$ *Top 3 Arranger*, as the main variable of interest. As before, the coefficient on *Relation Binary* remains negative and statistically significant, but the estimated interaction term is positive and statistically significant. This result is in conformity with the reputation hypothesis. Further analyses are conducted in Columns (2) and (3), which repeat the exercise in the first column replacing the binary measure with measures that capture the intensity of lending relationships. As depicted in these columns, while *Relation Number* and *Relation Amount* have negative and statistically significant coefficients, the terms for their interactions with reputation, *Relation Number* $\times$ *Top 3 Arranger* and *Relation Amount* $\times$ *Top 3 Arranger*, are positive and statistically significant. These regres-

regression. Instrumenting relationship with distance, they observe the coefficient for relationships increases approximately 5.1 times compared to OLS estimates.

8 According to McFadden (1974, 1978), values for pseudo R^2 ranging from 0.2 to 0.4 represent very good model fit.

sion analyses suggest that a reduction in the retained share, caused by a prior lending relationship, is concentrated in syndicates headed by less reputable lead arrangers.

This result suggests that the effect of lending relationships on the retained share depends on the degree of the lead arranger's reputation. That means, relationships have a varying effect in the sense that there is a level of a lead arranger's reputation beyond which relationships have a smaller retained-share effect. The concentration of the reduction of the retained share at the bottom of the lead arrangers' reputational spectrum suggests that reputation makes the importance of establishing relationships less relevant. This finding seems to support the idea that the impact of a relationship is more important in contracts in which lead–participant agency conflicts are high, and that as agency-problem-mitigation instruments, lead arrangers' reputation and relationships are not complementary.

The available evidence shows that the syndicated-loan market is dominated by large banks (see, e.g., Ross, 2010). This evidence may be construed as reflecting the concern on the part of syndicate participants about the small lead arrangers' screening and monitoring ability. Small lead arrangers may not provide enough screening and monitoring to convince participants to take part in the loans they arrange. Since relationships can facilitate screening and monitoring, one may thus ask whether establishing a lending relationship enables small lead arrangers to persuade participants that they can offer the necessary screening and monitoring. This section is thus explores whether the effect of lending relationships varies enough that the reduction in the retained share is more pronounced for small lead arrangers. To examine this idea, lending relationships are allowed to interact with a dichotomized variable that captures lead arrangers' size in the regression of the retained-share equation. The binary variable *Small Arranger* takes the value one if a lead arranger has less than the median total assets. In syndicated arrangements in which multiple lead arrangers are involved, this paper adopts the size of the lead arranger with the largest retained share.

Table 16. Variation by Lead Arrangers' Reputation and Size

This table reports regression results when relationship measures are allowed to interact with the lead arranger's reputation and size. Dependent variable is *Retained Share*. Columns (1)–(3) run the model using interactions between relationship measures and *Top 3 Arranger* where *Top 3 Arranger* identifies lead arrangers in the top 3% in terms of their market share in the syndicated-loan market. Columns (4)–(6) repeat the analysis using the interaction between relationship measures and *Small Arranger* where *Small Arranger* identifies lead arrangers whose total assets are below the sample median. All regressions control for loan type, purpose, industry and year dummies. Standard errors are heteroskedasticity robust and clustered at the borrower level. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Relation Binary × *Top 3 Arranger*	3.973***					
	(0.99)					
Relation Number × *Top 3 Arranger*		4.153***				
		(1.14)				
Relation Amount × *Top 3 Arranger*			3.105**			
			(1.23)			
Relation Binary × *Small Arranger*				−2.482**		
				(1.02)		
Relation Number × *Small Arranger*					−2.788**	
					(1.18)	
Relation Amount × *Small Arranger*						−3.210**
						(1.31)
Relation Binary	−3.634***			−1.156		
	(0.67)			(0.72)		
Relation Number		−3.612***			−0.785	
		(0.81)			(0.83)	
Relation Amount			−2.954***			−0.103
			(0.84)			(1.01)

(Continued on next page)

Table 16 Variation by Lead Arrangers' Reputation and Size (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Top 3 Arranger	−6.179***	−5.501***	−4.980***	−3.657***	−3.751***	−3.784***
	(0.85)	(0.76)	(0.76)	(0.54)	(0.54)	(0.54)
Small Arranger				0.941	0.540	0.703
				(1.48)	(1.41)	(1.43)
Arranger Size	−1.239***	−1.256***	−1.247***	−1.379**	−1.406***	−1.372**
	(0.39)	(0.39)	(0.39)	(0.54)	(0.54)	(0.55)
Opacity	1.650**	1.670**	1.723**	1.597*	1.600*	1.648**
	(0.82)	(0.82)	(0.82)	(0.82)	(0.82)	(0.82)
Firm Reputation	−0.555	−0.918**	−0.879**	−0.544	−0.936**	−0.888**
	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)
Firm Size	−1.759***	−1.774***	−1.780***	−1.748***	−1.774***	−1.772***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
Profitability	−1.214	−1.058	−1.128	−1.260	−0.968	−1.106
	(4.14)	(4.15)	(4.16)	(4.16)	(4.16)	(4.16)
Tangibility	−1.992	−2.087	−2.068	−1.993	−2.084	−2.041
	(1.40)	(1.40)	(1.41)	(1.41)	(1.41)	(1.41)
Leverage	−4.897***	−4.846**	−4.890***	−4.960***	−4.762**	−4.812**
	(1.89)	(1.89)	(1.89)	(1.89)	(1.89)	(1.89)
Financial Distress	1.316	1.367	1.315	1.320	1.345	1.302
	(0.86)	(0.86)	(0.86)	(0.86)	(0.86)	(0.86)
ln(*Loan Amount*)	−6.804***	−6.816***	−6.817***	−6.815***	−6.819***	−6.821***
	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)
ln(*Loan Maturity*)	−5.048***	−5.024***	−5.019***	−5.038***	−5.016***	−5.018***
	(0.56)	(0.57)	(0.57)	(0.56)	(0.56)	(0.56)
R^2	0.415	0.413	0.413	0.414	0.413	0.413
N	7,659	7,659	7,659	7,659	7,659	7,659

Consistent with a size-based interpretation, the analysis suggests that the effect is stronger for small lead arrangers, as can be seen from the results reported in the last three columns of Table 15. These columns show that the estimated coefficients on the measures of lending relationship continued to be significant and negative. Interestingly, the estimated coefficients of the interaction term *Relation Binary* $\times$ *Small Arranger* in Column (4), *Relation Number* $\times$ *Small Arranger* in Column(5) and *Relation Amount* $\times$ *Small Arranger* in Column (6) are also negative and significantly different from zero. This result thus clearly shows that lending relationships have more pronounced effects for small lead arrangers. On the basis of this result, one can conclude that small lead arrangers with relationships do not need to retain a larger share of the loans to these firms to induce participants to join in the loan.

4.5 *Relationship Effects: Opaque versus Transparent Firm*

The evidence to this point suggests that lead arrangers can build lending relationships to reduce the share they must retain. The theoretical discussion in Section 2, however, holds the argument that participants are potentially exposed to different degrees of agency conflicts based on the borrowing firm's information environment. More specifically, they may be subject to more severe agency conflicts in a sample of contractual arrangements with informationally opaque than transparent firms. This section thus tests whether the effect of lending relationships on the retained share differs between loan contracts with opaque and transparent firms. To this end, the syndicate arrangements in the sample are split into two groups on the basis of whether, or not, the firm has an S&P credit rating. *Opacity* identifies loan contracts with firms that do not have S&P credit ratings and is used to construct two interaction terms, *Relation Binary* $\times$ *Opacity* and *Relation Binary* $\times$ $(1 - \textit{Opacity})$. The applied estimation technique then involves running a regression model in which the two interaction terms are added as additional regressors and then testing the equality of the interaction coefficients. Table 17 presents the estimation results.

Table 17. Relationship Effects: Opaque versus Transparent Firm

This table presents results from the estimation of whether the impact of lending relationships on the retained share varies between syndicate arrangements with opaque and transparent firms. *Relation Binary* measures whether a previous lending relationship exists between the lead arranger and the borrower. *Opacity* identifies syndicate arrangements made with firms that do not have S&P credit ratings. *Small Firm* identifies contracts made with firms that have below the sample median sales at close. *Speculative Grade* identifies syndicated loans made to firms with S&P credit ratings between BB^{+} and C. The Δ interaction coeff presents results of tests of the differences between the interaction terms. All other variables are defined as in the Appendix. In all regressions, standard errors are heteroskedasticity robust and clustered at the firm level. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Retained Share		
	(1)	(2)	(3)
Relation Binary × *Opacity*	−2.578***		
	(0.72)		
Relation Binary × (1 − *Opacity*)	−2.231***		
	(0.73)		
Relation Binary × *Small Firm*		−1.858**	
		(0.80)	
Relation Binary × (1 − *Small Firm*)		−2.898***	
		(0.58)	
Relation Binary × *Speculative Grade*			−3.471***
			(1.09)
Relation Binary × (1 − *Speculative Grade*)			−2.233***
			(0.53)
Top 3 Arranger	−3.637***	−3.596***	−3.618***
	(0.54)	(0.54)	(0.54)
Arranger Size	−1.257***	−1.245***	−1.257***
	(0.39)	(0.39)	(0.39)
Opacity	1.771*	1.541*	1.231
	(1.05)	(0.82)	(0.86)
Firm Reputation	−0.528	−0.529	−0.498
	(0.44)	(0.44)	(0.44)
Firm Size	−1.745***	−1.615***	−1.774***
	(0.27)	(0.29)	(0.27)
Profitability	−1.381	−1.509	−1.519
	(4.16)	(4.15)	(4.16)
Tangibility	−2.058	−2.048	−2.075
	(1.41)	(1.41)	(1.41)
Leverage	−4.921***	−4.911***	−4.703**
	(1.89)	(1.89)	(1.92)
Financial Distress	1.347	1.329	1.328
	(0.86)	(0.86)	(0.86)

(Continued on next page)

Table 17. Relationship Effects: Opaque versus Transparent Firm (Continued)

	Retained Share		
	(1)	(2)	(3)
ln(*Loan Amount*)	-6.807^{***}	-6.802^{***}	-6.819^{***}
	(0.35)	(0.35)	(0.35)
ln(*Loan Maturity*)	-5.034^{***}	-5.030^{***}	-5.017^{***}
	(0.56)	(0.56)	(0.56)
Δ interaction coeff	-0.347	1.040	-1.238
	(1.02)	(0.92)	(1.08)
Loan-type dummies	YES	YES	YES
Loan-purpose dummies	YES	YES	YES
Industry dummies	YES	YES	YES
Year dummies	YES	YES	YES
R^2	0.413	0.413	0.413
N	7,659	7,659	7,659

The analysis suggests that lending relationships have the retained-share-reducing effect whether contracts are made with informationally opaque or transparent firms. This result is presented in Column (1) where the estimated coefficients of the two interaction terms are negative and statistically significant at the 1% level. Thus, the analysis suggests that involvement in lending relationships is associated with a reduction in the share held by lead arrangers organizing syndicated loans for both informationally opaque and transparent firms. The test of the equality of the coefficients on the two interaction terms, Δ interaction coeff, further shows that the two interaction coefficients are not statistically significantly different from one another. On the basis of this insignificant equality test of the interaction coefficients, one cannot reject the null hypothesis that a negative retained-share effect is equal in loan contracts with opaque and transparent firms.

Additional evidence on the causal invariance (i.e., the impact of relationships remains invariant between opaque and transparent firms) is also found by examining whether the effect of lending relationships on the retained share varies between syndicate arrangements made with small and large firms. This analysis is conducted by splitting syndicated loans in the sample into two groups based on the borrower's sales at close and constructing a binary variable, *Small Firm*, that identifies syndicate arrangements whose borrowers have below the sample median values of sales at close. The estimation technique then involves running a retained share model by adding to a regression specification the interaction terms *Relation Binary* $\times$ *Small Firm* and *Relation Binary* $\times$ $(1 - \textit{Small Firm})$ as additional independent variables. As shown in Column (2), both the interaction terms are significant and negatively related to the retained share. This result suggests that establishing lending relationships also lead to a smaller retained share for lead arrangers organizing syndicated loans for both small and large firms. Again, the test for interaction-coefficient equality, Δ interaction coeff, shows that the coefficients on the two interaction terms do not significantly differ from each other.

The analysis of whether the retained-share-reducing effect varies between syndicated loans whose borrowers have speculative- and nonspeculative-grade credit ratings provides additional evidence that the impact of lending relationships is causally invariant. This analysis is carried out by running a retained-share model that includes the interaction terms *Relation Binary* $\times$ *Speculative* and *Relation Binary* $\times$ $(1 - \textit{Speculative})$ as additional explanatory variables. The binary variable *Speculative* identifies contractual arrangements made with borrowing firms that have speculative-grade ratings, S&P credit ratings between BB^{+} and C. The reported result shows that both interaction terms have negative and statistically significant coefficients. This result shows that a lead arranger's lending relationship with a firm decreases the share it retains in a loan even when the loan is made to a firm with speculative-grade credit ratings. The interaction-coefficient comparability test, Δ interaction coeff, shows that the coefficients are not statistically significantly different from one another.

4.6 *Relationship Effects: Covenanted versus Uncovenanted Loans*

Two competing predictions were also raised in the theoretical discussion presented in Section 2 about the effect of lending relationships on the retained share in loan contracts that include covenants. One prediction suggests that exposure to agency conflicts is less in the sample of syndicated loan contracts that impose covenants. This prediction follows from the perspective that covenants limit borrowers' action sets, so participants should be exposed to less serious agency conflicts. The other prediction posits that exposure to severe agency problems are high in the sample of loan contracts that include covenants. This is because in contracts that include covenants, the borrower's compliance with the imposed restrictions requires monitoring, and hence a high potential for shirking.

To test these competing predictions, this section examines whether the effect of lending relationships on the retained share varies between covenanted and uncovenanted loans. Towards this end, syndicated loans in the sample are divided into two facility groups: those facilities in which covenants are included and those facilities in which covenants are not included. Using the dummy variable *Covenant* to identify loan contracts that impose covenants, the study constructs two interaction terms, *Relation Binary* $\times$ *Covenant* and *Relation Binary* $\times$ $(1 - \textit{Covenant})$. The adopted estimation method involves running a retained-share model that includes the two interaction terms and then testing the comparability of the interaction coefficients.[9] Table 18 reports the estimation results.

The analysis indicates that relationships have stronger retained-share reducing effects in loan contracts that include covenants. As is evident from an inspection of the results reported in Column (1), while the estimated coefficient of the interaction term *Relation Binary* $\times$ *Covenant* is significantly negative, the estimated coefficient on the interaction term *Relation Binary* $\times$ $(1 - \textit{Covenant})$ is not statistically significantly different from zero. This result suggests that lending relationships serve as an important factor in terms of reducing the retained share in loan contracts that include covenants. The test of the comparison of the coefficients of the two interaction terms, Δ interaction coeff, rejects the null hypothesis of the equality of the coefficients. This test suggests that the retained-share-reducing effect

9 In unreported results, I split the sample into two on the basis of whether loan contracts include covenants and ran two separate regressions using covenanted and uncovenanted loans. The coefficients on *Relation Binary* in the two regression models were significantly different.

of a lending relationship is substantially stronger in loan contracts that include covenants. It thus appears that covenants that restrict borrowers' actions do not make the importance of relationships less relevant.

The above finding also holds when examining whether the retained share effect of relationships varies between loans that include performance covenants and all other facilities. This analysis is motivated by research suggesting that performance covenants are particularly included in loan contracts to increase the lender's incentive to monitor borrowers (Christensen and Nikolaev, 2012). To conduct the analysis, the estimated model includes two interaction terms, $\textit{Relation Binary} \times \textit{P.Covenant}$ and $\textit{Relation Binary} \times (1 - \textit{P.Covenant})$. The dummy variable *P.Covenant* identifies contracts that include performance covenants. As the second column reports, the coefficient on the interaction term $\textit{Relation Binary} \times \textit{P.Covenant}$ is negative and statistically significant. In contrast, the estimated coefficient of the interaction term $\textit{Relation Binary} \times (1 - \textit{P.Covenant})$ is not statistically significant. Δ interaction coeff also rejects the null hypothesis of the equality of the coefficients. This finding suggests that the effect of lending relationships is more pronounced in syndicated loan contracts that impose performance covenants.

In Column (3), I repeat the regression analysis in the first column for the sample of firms with investment-grade credit ratings, S&P long-term issuer ratings BBB^{-} or above. As can be observed from the results reported in the third column, while the term $\textit{Relation Binary} \times \textit{Covenant}$ is statistically significant, the estimates of the interaction term $\textit{Relation Binary} \times (1 - \textit{Covenant})$ is not statistically significantly different from zero. The test of the coefficient equality of the interaction terms, Δ interaction coeff, rejects the null hypothesis that the coefficients are not distinct from each other. This result indicates that lending relationships are associated with a reduction in the retained share for loan contracts that include covenants even when the borrowers are high-quality firms.

Table 18. Relationship Effects: Covenanted versus Uncovenanted Loans

This table provides results from the estimation of whether the effect of relationships on the retained share varies between covenanted and uncovenanted loans. Columns (1) and (2) report the coefficient estimates for the full sample. Columns (3) repeats the analysis for loan contracts made with firms that have S&P credit ratings between AAA and BBB^{-}, whereas Columns (4) and (5) report the results when the firms have credit ratings between BB^{+} and C. *Covenant* and *P.Covenant* identify contracts that include any covenants and performance covenants, respectively. Δ interaction coeff presents results of tests of the differences between the interaction terms. Standard errors are heteroskedasticity robust and clustered at the firm level. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Retained Share				
	Full sample		High S&P ratings	Low S&P ratings	
	(1)	(2)	(3)	(4)	[5]
Relation Binary × *Covenant*	−3.130***		−2.220***	−6.081***	
	(0.57)		(0.68)	(1.42)	
Relation Binary × (1 − *Covenant*)	−0.733		−0.390	−0.065	
	(0.78)		(0.89)	(3.71)	
Relation Binary × *P.Covenant*		−3.348***			−6.398***
		(0.60)			(1.43)
Relation Binary × (1 − *P.Covenant*)		−1.028			−0.209
		(0.65)			(3.02)
Top 3 Arranger	−3.661***	−3.653***	−1.147**	−4.156***	−4.198***
	(0.54)	(0.54)	(0.58)	(1.51)	(1.52)
Arranger Size	−1.235***	−1.250***	−2.190***	−1.780*	−1.706*
	(0.39)	(0.39)	(0.60)	(0.93)	(0.93)
Opacity	1.563*	1.705**	0.000	0.000	0.000
	(0.82)	(0.82)	(.)	(.)	(.)
Firm Reputation	−0.551	−0.545	−0.461	0.015	0.025
	(0.44)	(0.44)	(0.42)	(1.15)	(1.15)
Firm Size	−1.776***	−1.792***	−0.764**	−0.746	−0.691

(Continued on next page)

Table 18 Relationship Effects: Covenanted versus Uncovenanted Loans (Continued)

	Retained Share				
	Full sample		High S&P ratings	Low S&P ratings	
	(1)	(2)	(3)	(4)	[5]
	(0.27)	(0.27)	(0.35)	(0.61)	(0.62)
Profitability	−1.501	−1.362	7.305	−5.227	−4.654
	(4.16)	(4.15)	(6.26)	(9.71)	(9.69)
Tangibility	−2.079	−2.201	−3.766**	5.136*	4.870
	(1.41)	(1.42)	(1.82)	(3.07)	(3.08)
Leverage	−4.898***	−4.610**	0.793	8.649*	9.070**
	(1.89)	(1.89)	(2.67)	(4.67)	(4.62)
Financial Distress	1.334	1.279	−1.208	0.226	0.239
	(0.86)	(0.86)	(0.92)	(1.83)	(1.82)
ln(*Loan Amount*)	−6.787***	−6.794***	−3.814***	−5.570***	−5.569***
	(0.35)	(0.35)	(0.62)	(0.86)	(0.86)
ln(*Loan Maturity*)	−4.974***	−4.951***	−7.132***	−4.357***	−4.146***
	(0.56)	(0.56)	(1.34)	(1.42)	(1.43)
Δ interaction coeff	−2.397***	−2.320***	−1.830**	−6.016	−6.188**
	(0.83)	(0.70)	(0.78)	(3.69)	(3.01)
Loan-type dummies	YES	YES	YES	YES	YES
Loan-purpose dummies	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
R^2	0.414	0.414	0.322	0.266	0.267
N	7,659	7,659	2,117	1,319	1,319

The last two columns repeat the previous exercises on the sample of borrowers with speculative-grade credit ratings (i.e., S&P long-term issuer ratings between BB^{+} and C). As reported in column (4), the coefficient on *Relation Binary* $\times$ *Covenant* is significantly negative, while the coefficient on *Relation Binary* $\times$ $(1 - \textit{Covenant})$ is statistically insignificant. A test of the equality of the interaction coefficients, however, cannot reject the null hypothesis that the two interaction terms are not significantly distinct from each other. The result presented in Column (5) shows that while the coefficient on *Relation Binary* $\times$ *P.Covenant* is negatively and significantly estimated, the estimate of the coefficient on *Relation Binary* $\times$ $(1 - \textit{P.Covenant})$ is not significantly different from zero. Δ interaction coeff, shows that the interaction terms are significantly different. Overall, this analysis suggests that lending relationships are associated with a significantly stronger reduction in the retained share among loan contracts that include covenants.

5 ADDITIONAL ROBUSTNESS TESTS

For this analysis, I conducted robustness checks of the results to potential endogeneity problems associated with lending-relationship formation using alternative estimation techniques that correct for endogeneity bias. However, some potential concerns related to other factors may still remain. These additional concerns are more likely related to the method applied in this paper to construct lending-relationship measures. This section, thus, performs two additional robustness tests to dissipate these additional potential concerns.

5.1 *Multiple Lead Arrangers*

One potential concern is that the reduction in the retained share may be related to the number of lead arrangers in a loan facility. The argument here is that some syndicated lending arrangements are headed by multiple lead arrangers. It is likely that multiple lead arrangers increase the likelihood of a syndicated loan being arranged by a lead

Table 19. The Effect of Relationships on the Retained Share: Evidence from Facilities with A Single Lead Arranger

This table reports the regression results of the effects of lending relationships on the percentage of a syndicated loan retained by the lead arranger (*Retained Share*). The results reported in Columns (1)–(3) are obtained from the sample of syndicated loans headed by a single lead arranger. *Relation Binary* indicates whether lending relationships exist between the lead arranger and the borrower of a loan. *Relation Number* accounts for the proportion of previous lending relationships in terms of the number of interactions. *Relation Amount* capture the proportion of previous lending relationships in terms of the amount of interactions. All other variables are defined in the Appendix. In all regressions, standard errors are heteroskedasticity robust and clustered at the firm level. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Retained Share		
	(1)	(2)	(3)
Relation Binary	-2.022^{***}		
	(0.62)		
Relation Number		-2.131^{***}	
		(0.75)	
Relation Amount			-2.253^{***}
			(0.74)
Top 3 Arranger	-4.179^{***}	-4.210^{***}	-4.179^{***}
	(0.70)	(0.70)	(0.70)
Arranger Size	-0.847^{*}	-0.852^{*}	-0.853^{*}
	(0.44)	(0.44)	(0.44)
Opacity	0.093	0.118	0.176
	(0.94)	(0.94)	(0.94)
Firm Reputation	-0.711	-1.030^{**}	-0.995^{*}
	(0.51)	(0.51)	(0.51)
Firm Size	-1.853^{***}	-1.876^{***}	-1.877^{***}
	(0.30)	(0.30)	(0.30)
Profitability	-1.152	-0.874	-0.991
	(4.80)	(4.80)	(4.80)
Tangibility	-1.089	-1.125	-1.114
	(1.67)	(1.67)	(1.67)
Leverage	-6.786^{***}	-6.651^{***}	-6.735^{***}
	(2.16)	(2.15)	(2.15)
Financial Distress	1.584	1.599	1.564
	(1.07)	(1.06)	(1.07)
ln(*Loan Amount*)	-7.942^{***}	-7.941^{***}	-7.930^{***}
	(0.39)	(0.39)	(0.39)
ln(*Loan Maturity*)	-4.722^{***}	-4.687^{***}	-4.684^{***}
	(0.66)	(0.66)	(0.66)
Loan-type dummies	YES	YES	YES
Loan-purpose dummies	YES	YES	YES
Industry dummies	YES	YES	YES
Year dummies	YES	YES	YES
R^2	0.412	0.411	0.412
N	5,583	5,583	5,583

arranger with whom the borrower has lending relationships. This follows simply because more than one lead arranger have a higher likelihood than one lead arranger of having existing lending relationships with the firm. One may thus expect a positive correlation between a measure of lending relationships (*Relation Binary*) and the likelihood that a loan has more than one lead arranger. This, in turn, means that the presence of multiple lead arrangers could ultimately drive the association between *Relation Binary* and *Retained Share*. In this situation, the observed reduction in the retained share may reflect the effect of the number of lead arrangers rather than the effect of lending relationships, or both.

The analysis shows that excluding those facilities that are provided by multiple lead arrangers from the sample does not seem to affect the previously established results. As Table 19 depicts, the estimated coefficients of lending-relationship measures are still negative and significantly different from zero. Thus, even though it is plausible that having multiple lead arrangers can affect the retained share, the present finding clearly suggests an effect of lending relationships. These negative coefficients suggest that even in loan facilities organized by a single lead arranger, building lending relationships with firms enables lead arrangers to retain a smaller share.

5.2 *Fixed Effects and Clustering*

The analysis discussed so far runs regressions clustering by firms to adjust standard errors for potential correlation between observations of the same borrowing firm. An alternative approach that can also handle the possibility of correlation among observations within firm is firm fixed effects. Including firm fixed effects has also an additional benefit in that it controls for potential endogeneity stemming from firm-level unobservables. To test the robustness of the baseline regression results to this alternative specification, this section reestimates the retained-share regression model with a firm fixed-effect dummy. Table 20 reports the results from the regression specification featuring a firm-level fixed-effect dummy. As can be seen from Column (1), the introduction of a firm-level fixed-effect dummy leads to a small reduction in the coefficient of the *Relation Binary* in comparison to the OLS estimates reported in Table 13. Nevertheless, this result also shows that lending relationships have a significant negative effect on the retained share. The analysis in Column (2) adds clustering by firms in a regression that includes a firm-level fixed-effect dummy. As one expects, clustering leaves the coefficient estimates of *Relation Binary* unchanged. While the standard errors increased to some extent with clustering by firms, the finding, however, shows that clustering did not make lending relationships' impact on the retained share less statistically significant.

The robustness analysis reported above determines if controlling for potential correlation across observations for a firm that arises from firm-level persistent attributes changes the statistical significance of lending relationships' impact on the retained share. One may also argue that a lead-arranger–level effect (i.e., persistent lead arranger attributes) could also drive correlation across observations between firms. To check the sensitivity of the statistical significance of the results to this possibility, clustering by a lead arranger is added to the retained-share regression model that includes a firm-level fixed-effect dummy. As can be noted from Column (3), clustering by lead arrangers increases the standard errors. But lending relationship's impact is still significant at the 5% level. Moreover, introducing a lead-arranger–level fixed-effect dummy enables one to effectively address omitted-variable bias in addition to accounting for potential correlation across observations. Thus, to further check the robustness of a lending relationship estimate and its statistical significance, the analysis in Column (4) involves estimating a regression model that includes a lead-arranger fixed-effect dummy and clustering by firms. As the reported result shows, this specification yields the estimate of lending relationships that is very similar to those reported in the previous column.

The set of robustness results reported in Columns (2)–(4) of Table 20 is obtained from specifications that include clustering at either a firm level or a lead-arranger level. However, it could also be the case that there may be correlation between observations within a firm and

Table 20. The Effect of Relationships on the Retained Share: Fixed Effects and Clustering

This table presents the regression results of the impact of relationships on the percentage share of a syndicated loan retained by the lead arranger (*Retained Share*). While Columns (1)–(3) report results obtained from regressions with a firm fixed-effect dummy, Column [4] present results of a regression with a lead-arranger fixed-effect dummy. *Relation Binary* indicates whether a prior lending relationship exists between the lead arranger and the borrower of a loan. All other variables are defined in the Appendix. In Columns (2)–(4), standard errors are clustered at either the firm or lead-arranger level, whereas in the last column the standard errors are clustered at the firm and lead-arranger levels simultaneously. In all regressions, standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Retained Share				
		Firm FE,	Firm FE,	Lead FE	Clust. by firm
	Firm FE,	Clust. by firm	Clust. by lead	Clust. by firm	Clust. by lead
	(1)	(2)	(3)	(4)	(5)
Relation Binary	-1.933^{***}	-1.933^{***}	-1.933^{**}	-2.112^{***}	-2.429^{***}
	(0.52)	(0.66)	(0.73)	(0.50)	(0.64)
Top 3 Arranger	-3.108^{***}	-3.108^{***}	-3.108^{***}	-2.675^{***}	-3.626^{***}
	(0.59)	(0.85)	(0.56)	(0.56)	(0.45)
Arranger Size	-0.976^{*}	-0.976	-0.976	0.532	-1.254^{*}
	(0.51)	(0.69)	(0.83)	(0.57)	(0.76)
Opacity	-1.902	-1.902	-1.902^{**}	1.154	1.577^{**}
	(1.17)	(1.72)	(0.80)	(0.79)	(0.62)
Firm Reputation	-0.050	-0.050	-0.050	-0.663	-0.524
	(0.44)	(0.60)	(0.43)	(0.42)	(0.38)
Firm Size	-1.447	-1.447	-1.447	-1.704^{***}	-1.745^{***}
	(0.95)	(1.39)	(1.41)	(0.26)	(0.25)
Profitability	-10.519^{**}	-10.519	-10.519^{***}	-1.720	-1.386
	(5.15)	(6.90)	(3.88)	(4.02)	(5.03)
Tangibility	1.152	1.152	1.152	-1.201	-2.054
	(3.80)	(5.34)	(5.25)	(1.34)	(1.52)
Leverage	-3.386	-3.386	-3.386	-6.245^{***}	-4.928^{***}
	(2.75)	(3.73)	(3.56)	(1.75)	(1.88)
Financial Distress	0.335	0.335	0.335	1.303	1.339
	(0.90)	(1.24)	(0.62)	(0.81)	(1.23)
ln(*Loan Amount*)	-4.639^{***}	-4.639^{***}	-4.639^{***}	-6.670^{***}	-6.807^{***}
	(0.39)	(0.51)	(0.35)	(0.34)	(0.65)
ln(*Loan Maturity*)	-3.869^{***}	-3.869^{***}	-3.869^{***}	-5.050^{***}	-5.034^{***}
	(0.55)	(0.71)	(0.56)	(0.55)	(0.62)
Loan-type dummies	YES	YES	YES	Yes	YES
Loan-purpose dummies	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	NO	NO
Lead fixed effect	YES	NO	NO	YES	NO
R^2	0.732	0.732	0.732	0.448	0.413
N	7,659	7,659	7,659	7,659	7,659

within a lead arranger. In such situations, where there exists simultaneous correlations in two dimensions, Thompson (2011) shows that the usual one-dimensional clustering technique does not correctly adjust standard errors. As an additional robustness check to this possibility, this section uses a two-dimensional clustering approach that Thompson (2011) and Cameron et al. (2011) recently introduced and reruns the regression clustering by firms and lead arrangers. As shown in Column (5), this specification does not affect the statistical significance of the result reported in Table 13.

6 CONCLUSION

Syndicated lending has gained increasing popularity: A group of lenders jointly provide large loans to a firm on the basis of a single contract. Together with increasing popularity, however, has also come concerns about whether the potential information asymmetry stemming from the lead arrangers' lending relationships with borrowers introduces agency problems between a lead arranger and participants. Although the literature argues that lending relationships can influence the share retained by lead arrangers, which is used to certify the quality of a loan, the literature offers conflicting predictions. While a lending relationship can reduce the retained share by facilitating monitoring, it can also facilitate the exploitation of participants, thus increasing the lead arrangers' retained share.

I empirically examine the association between lead arrangers' lending relationships with firms and the share they retain in loans to them. Using prior interactions to measure lending relationships, my results strongly indicate that forging relationships decreases lead arrangers' retained share. Since lead arrangers claim less than entire loan they originate, it is possible that they may endogenously develop weak incentives for costly investments in choosing optimal monitoring efforts. If, however, lending relationships reduces the costs of monitoring, lead arrangers may still optimally invest in monitoring. Consequently, as the results in this analysis suggests, participants do not seem to provide relationship lead arrangers with the necessary monitoring incentives by way of insisting they retain a larger share.

The cross-sectional analysis presents results that further reduce concerns that lending relationships may introduce agency conflicts. The evidence shows that the negative effect of lending relationships on the retained share is stronger in syndicate arrangements headed by less reputable and small lead arrangers. Informationally opaque and high-risk borrowers would provide an ideal opportunity for relationship lead arrangers to exploit syndicate participants. The observed reduction in the share retained by relationship lead arrangers in contractual arrangements involving opaque firms, small firms, and firms with speculative-grade ratings suggests that postcontractual conflicts are more important than precontractual conflicts in loan syndication. As such, although loans to these firms require intensive monitoring, relationship lead arrangers are not required to hold a larger share; their monitoring-cost advantages seem to be sufficient. In fact, the negative effect of lending relationships is concentrated in loan contracts that include covenants—contracts that presumably require closer monitoring and, hence, the benefit of relationships.

REFERENCES

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267.

Abadie, A. and Imbens, G. W. (2008). On the failure of the bootstrap for matching estimators. *Econometrica*, 76(6):1537–1557.

Akiyoshi, F. and Minamihashi, N. (2014). The effect of bilateral lending relationships on syndicated loans: Evidence from Japan. Technical report, Centre for Finance.

Alexandre, H., Bouaiss, K., and Refait-Alexandre, C. (2014). Banking relationships and syndicated loans during the 2008 financial crisis. *Journal of Financial Services Research*, 46(1):99–113.

Allen, F. (1981). The prevention of default. *Journal of Finance*, 36(2):271–76.

Allen, T. (1990). Developments in the international syndicated loan market in the 1980s. *Quarterly Bulletin, Bank of England, February*, pages 71–77.

Altman, E. I. (1968). Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4):589–609.

Amershi, A. H. and Stoeckenius, J. H. W. (1983). The theory of syndicates and linear sharing rules. *Econometrica*, 51(5):1407–1416.

Armstrong, J. (2003). The syndicated loan market: Developments in the North American context. Technical report, Bank of Canada. Working Paper 2003-15.

Aslan, H. (2015). Do lending relationships affect corporate financial policies? *Financial Management*, 45(1):141–173.

Baliga, S. (1999). Monitoring and collusion with "soft" information. *Journal of Law, Economics and Organization*, 15(2):434–40.

Beneish, M. D. and Press, E. (1993). Costs of technical violation of accounting-based debt covenants. *Accounting Review*, 68(2):233–257.

Beneish, M. D. and Press, E. (1995). The resolution of technical default. *Accounting Review*, 70(2):337–353.

Benston, G. J. (1994). Universal banking. *Journal of Economic Perspectives*, 8(3):121–144.

Berg, T., Saunders, A., and Steffen, S. (2016). The total cost of corporate borrowing in the loan market: Don't ignore the fees. *Journal of Finance*, 71(3):1357–1392.

Berlin, M. and Loeys, J. (1988). Bond covenants and delegated monitoring. *Journal of Finance*, 43(2):397–412.

Berlin, M. and Mester, L. J. (1992). Debt covenants and renegotiation. *Accounting Review*, 2(2):95–133.

Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A. (2007). So what do I get? The bank's view of lending relationships. *Journal of Financial Economics*, 85(2):368–419.

Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A. (2011). Lending relationships and loan contract terms. *Review of Economic Studies*, 24(4):1141–1203.

Bolton, P. and Scharfstein, D. S. (1990). A theory of predation based on agency problems in financial contracting. *American Economic Review*, 80(1):93–106.

Bolton, P. and Scharfstein, D. S. (1996). Optimal debt structure and the number of creditors. *Journal of Political Economy*, 104(1):1–25.

Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9(1):7–25.

Boot, A. W. A. and Thakor, A. V. (2000). Can relationship banking survive competition? *Journal of Finance*, 55(2):679–713.

Bosch, O. and Steffen, S. (2007). Informed lending and the structure of loan syndicates – Evidence from the European syndicated loan market. *Goethe University Frankfurt*.

Brander, J. A., Amit, R., and Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, 11(3):423–452.

Bushman, R. M. and Wittenberg-Moerman, R. (2012). The role of bank reputation in "certifying" future performance implications of borrowers' accounting numbers. *Journal of Accounting Research*, 50(4):883–930.

Cai, J. (2010). Competition or collaboration? The reciprocity effect in loan syndication. Technical report, FRB of Cleveland. Policy Discussion Paper No. 09-09R.

Cai, J., Saunders, A., and Steffen, S. (2014). Syndication, interconnectedness, and systemic risk. Technical report, European School of Management and Technology.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business and Economic Statistics*, 29(2):238–249.

Campbell, T. S. and Kracaw, W. A. (1980). Information production, market signalling, and the theory of financial intermediation. *Journal of Finance*, 35(4):863–882.

Cerulli, G. (2014). ivtreatreg: A command for fitting binary treatment models with heterogeneous response to treatment and unobservable selection. *Stata Journal*, 14(3):453–480.

Champagne, C. and Kryzanowski, L. (2007). Are current syndicated loan alliances related to past alliances? *Journal of Banking & Finance*, 31(10):3145–3161.

Chaudhry, S. and Kleimeier, S. (2013). Information asymmetry and the structure of loan syndicates. Technical report, University of Birmingham. Discussion Paper.

Chava, S. and Roberts, M. R. (2008). How does financing impact investment? The role of debt covenants. *Journal of Finance*, 63(5):2085 –2121.

Chemmanur, T. J. and Fulghieri, P. (1994). Investment bank reputation, information production, and financial intermediation. *Journal of Finance*, 49(1):57–79.

Chen, K. C. W. and Wei, K. C. J. (1993). Creditors' decisions to waive violations of accounting-based debt covenants. *Accounting Review*, 68(2):218–232.

Chowdhry, B. and Nanda, V. K. (1983). Stabilization, syndication, and pricing of IPOs. *Journal of Financial and Quantitative Analysis*, 31(01):25–42.

Christensen, H. B. and Nikolaev, V. V. (2012). Capital versus performance covenants in debt contracts. *Journal of Accounting Research*, 50(1):75–116.

Chui, M., Domanski, D., Kugler, P., and Shek, J. (2010). The collapse of international bank finance during the crisis: Evidence from syndicated loan markets. *BIS Quarterly Review, September*, pages 39—49.

Cochran, W. G. and Rubin, D. B. (1973). Controlling bias in observational studies: A review. *Sankhyā: The Indian Journal of Statistics, Series A*, 35(4):417–446.

Dahiya, S., Saunders, A., and Srinivasan, A. (2003). Financial distress and bank lending relationships. *Journal of Finance*, 58(1):375–399.

Das, S. R. and Nanda, A. (1999). A theory of banking structure. *Journal of Banking & Finance*, 23(6):863–895.

Dass, N. and Massa, M. (2011). The impact of a strong bank–firm relationship on the borrowing firm. *Review of Financial Studies*, 24(4):1204–1260.

DeFond, M. L. and Jiambalvo, J. (1994). Debt covenant violation and manipulation of accruals. *Journal of Accounting and Economics*, 17(1–2):145–176.

Demiroglu, C. and James, C. M. (2010). The information content of bank loan covenants. *Review of Economic Studies*, 23(10):3700–3737.

Demsetz, H. and Lehn, K. (1985). The structure of corporate ownership: Causes and consequences. *Journal of Political Economy*, 93(6):1155–1177.

Demski, J. S. and Sappington, D. E. M. (1987). Hierarchical regulatory control. *RAND Journal of Economics*, 18(3):369–383.

Denis, D. J. and Wang, J. (2014). Debt covenant renegotiations and creditor control rights. *Journal of Financial Economics*, 113(3):348–367.

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

Detragiache, E., Garella, P., and Guiso, L. (2000). Multiple versus single banking relationships: Theory and evidence. *Journal of Finance*, 55(3):1133–1161.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies*, 51(3):393–414.

Diamond, D. W. (1989). Reputation acquisition in debt markets. *Journal of Political Economy*, 97(4):828–862.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, 99(4):689–721.

Do, V. and Vu, T. (2010). The effects of reputation and relationships on lead banks' certification roles. *Journal of International Financial Markets, Institutions and Money*, 20(5):475–489.

Dye, R. A. (1986). Optimal monitoring policies in agencies. *RAND Journal of Economics*, 17(3):339–350.

Esty, B. C. (2001). Structuring loan syndicates: A case study of the Hong Kong Disneyland project loan. *Journal of Applied Corporate Finance*, 14(3):80–95.

François, P. and Missonier-Piera, F. (2007). The agency structure of loan syndicates. *Financial Review*, 42(2):227–245.

Gadanecz, B. (2004). The syndicated loan market: Structure, development and implications. *BIS Quarterly Review*, 2004(December):74–89.

Gadanecza, B., Karab, A., and Molyneux, P. (2012). Asymmetric information among lending syndicate members and the value of repeat lending. *Journal of International Financial Markets, Institutions and Money*, 22(4):913–935.

Gârleanu, N. and Zwiebel, J. (2009). Design and renegotiation of debt covenants. *Review of Financial Studies*, 22(2):749–781.

Gertner, R. and Scharfstein, D. (1991). A theory of workouts and the effects of reorganization law. *Journal of Finance*, 46(4):1189–1222.

Godlewski, C. J., Sanditov, B., and Burger-Helmchen, T. (2012). Bank lending networks, experience, reputation, and borrowing costs: Empirical evidence from the French syndicated lending market. *Journal of Business Finance & Accounting*, 39(1–2):113–140.

Gopalan, R., Nanda, V., and Yerramilli, V. (2011a). Does poor performance damage the reputation of financial intermediaries? Evidence from the loan syndication market. *Journal of Finance*, 66(6):2083–2120.

Gopalan, R., Udell, G. F., and Yerramilli, V. (2011b). Why do firms form new banking relationships? *Journal of Financial and Quantitative Analysis*, 46(05):1335–1365.

Gow, I. D., Ormazabal, G., and Taylor, D. J. (2010). Correcting for cross-sectional and time-series dependence in accounting research. *Accounting Review*, 85(2):483–512.

Gu, X. S. and Rosenbaum, P. R. (1993). Comparison of multivariate matching methods: Structures, distances, and algorithms. *Journal of Computational and Graphical Statistics*, 2(4):405–420.

Haubrich, J. G. (1989). Financial intermediation: Delegated monitoring and long-term relationships. *Journal of Banking & Finance*, 13(1):9–20.

Heckman, J. J. (1978). Dummy endogenous variables in a simultaneous equation system. *Econometrica*, 46(4):931–959.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1):153–161.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies*, 64(4):605–654.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1998). Matching as an econometric evaluation estimator. *Review of Economic Studies*, 65(2):261–294.

Hirshleifer, D. and Thakor, A. V. (1992). Managerial conservatism, project choice, and debt. *Review of Financial Studies*, 5(3):437–470.

Holmstrom, B. (1979). Moral hazard and observability. *Bell Journal of Economics*, 10(1):74–91.

Holmstrom, B. (1982). Moral hazard in teams. *Bell Journal of Economics*, 13(2):324–340.

Imbens, G. W. and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1):5–86.

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

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Jones, J. D., Lang, W. W., and Nigro, P. J. (2005). Agent bank behavior in bank loan syndications. *Journal of Financial Research*, 28(3):385–402.

Krasa, S. and Villamil, A. P. (1992). Monitoring the monitor: An incentive structure for a financial intermediary. *Journal of Economic Theory*, 57(1):197–221.

Leland, H. E. and Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. *Journal of Finance*, 32(2):371–387.

Leuven, E. and Sianesi, B. (2003). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Technical report, Stata. This version 4.0.11, 22 October 2014.

Lim, J., Minton, B. A., and Weisbach, M. S. (2014). Syndicated loan spreads and the composition of the syndicate. *Journal of Financial Economics*, 111(3):45–69.

Lockett, A. and Wright, M. (2001). The syndication of venture capital investments. *Omega*, 29(5):375–390.

Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press, Cambridge.

Marco and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching estimators. *Journal of Economic Surveys*, 22(1):31–72.

McCahery, J. and Schwienbacher, A. (2010). Bank reputation in the private debt market. *Journal of Corporate Finance*, 16(4):498–515.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., editor, *Frontiers in Econometrics*, pages 105–142. Academic Press, New York.

McFadden, D. (1978). Quantitative methods for analyzing travel behaviour of individuals: Some recent developments. In Hensher, D. and Stopher, P., editors, *Behavioural Travel Modelling*, pages 279–318. Croom Helm, London.

Nini, G., Smith, D. C., and Sufi, A. (2012). Creditor control rights, corporate governance, and firm value. *Review of Financial Studies*, 25(6):1713–1761.

Nitani, M. and Riding, A. (2013). Fund size and the syndication of venture capital investments. *Venture Capital*, 15(1):53–75.

Ordoñez, G. L. (2013). Fragility of reputation and clustering of risk-taking. *Theoretical Economics*, 8:653–700.

Panyagometh, K. and Roberts, G. S. (2010). Do lead banks exploit syndicate participants? Evidence from ex post risk. *Financial Management*, 39(1):273–299.

Petersen, M. A. (1999). Banks and the role of lending relationships: Evidence from the U.S. experience. *Rassegna Economica*, 63(1):37–61.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1):435–480.

Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? The information revolution in small business lending. *Journal of Finance*, 57(6):2533–2570.

Pichler, P. and Wilhelm, W. (2001). A theory of the syndicate: Form follows function. *Journal of Finance*, 56(6):2237–2264.

Qu, C. (2000). The fiduciary role of the manager and the agent in a loan syndicate. *Bond Law Review*, 12(1):86–105.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance*, 47(4):1367–1400.

Roberts, M. R. and Sufi, A. (2009a). Control rights and capital structure: An empirical investigation. *Journal of Finance*, 64(4):1657–1695.

Roberts, M. R. and Sufi, A. (2009b). Renegotiation of financial contracts: Evidence from private credit agreements. *Journal of Financial Economics*, 93(2):159–184.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Ross, D. G. (2010). The dominant bank effect: How high lender reputation affects the information content and terms of bank loans. *Review of Financial Studies*, 23(7):2730–2756.

Rubin, D. B. (1973). Matching to remove bias in observational studies. *Biometrics*, 29(1):159–183.

Rubin, D. B. (1980). Bias reduction using Mahalanobis-metric matching. *Biometrics*, 36(2):293–298.

Rubin, D. B. and Thomas, N. (1996). Matching using estimated propensity scores: Relating theory to practice. *Biometrics*, 52(1):249–264.

Ryan, R. H. J. (2009). The role of lead counsel in syndicated lending transactions. *Business Lawyer*, 64(3):783–800.

Santos, J. A. C. (1998). Commercial banks in the securities business: A review. *Journal of Financial Services Research*, 14(1):35–60.

Schaffer, M. E. (1989). The credible-commitment problem in the center-enterprise relationship. *Journal of Comparative Economics*, 13(3):359–382.

Schenone, C. (2004). The effect of banking relationships on the firm's IPO underpricing. *Journal of Finance*, 59(6):2903–2958.

Schenone, C. (2010). Lending relationships and information rents: Do banks exploit their information advantages? *Review of Financial Studies*, 23(3):1149–1199.

Schure, P., Scoones, D., and Gu, Q. (2005). A theory of loan syndication. *Finance Research Letters*, 2(3):165–172.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance*, 45(4):1069–1087.

Shleifer, A. and Vishny, R. (1997). A survey of corporate governance. *Journal of Finance*, 52(2):737–783.

Simons, K. (1993). Why do banks syndicate loans? *New England Economic Review of the Federal Reserve Bank of Boston*, pages 45–52.

Smith, C. W. J. (1993). A perspective on accounting-based debt covenant violations. *Accounting Review*, 68(2):289–303.

Smith, C. W. J. and Warner, J. B. (1979). On financial contracting: An analysis of bond covenants. *Journal of Financial Economics*, 7(2):117–161.

Stiglitz, J. E. and Weiss, A. (1983). Incentive effects of terminations: Applications to the credit and labor markets. *American Economic Review*, 73(5):912–927.

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

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics*, 99(1):1–10.

Townsend, R. M. (1979). Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory*, 21(2):265–293.

Tykvová, T. (2007). Who chooses whom? Syndication, skills and reputation. *Review of Financial Economics*, 16(1):5–28.

Von Thadden, E.-L. (1995). Long-term contracts, short-term investment and monitoring. *Review of Economic Studies*, 62(4):557–575.

Wang, T. Y., Winton, A., and Yu, X. (2010). Corporate fraud and business conditions: Evidence from IPOs. *Journal of Finance*, 56(6):2255–2292.

Welch, I. and Bris, A. (2005). The optimal concentration of creditors. *Journal of Finance*, 60(5):2193–2212.

Williamson, S. D. (1987). Costly monitoring, loan contracts, and equilibrium credit rationing. *Quarterly Journal of Economics*, 102(1):135–345.

Wilson, R. (1968). The theory of syndicates. *Econometrica*, 36(1):119–132.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge.

Appendix: Variable Definitions

Table 21. Variable Definitions

Variable	Definition
Retained Share	The percentage of a syndicated loan retained by the lead arranger
Relation Binary	A dummy variable: one if the lead arranger and the borrower have a prior lending interaction in the last five years
Relation Number	The ratio of the number of times the lead arranger and the borrower have interacted in the last five years to the total number of loans the borrower has taken during the same period
Relation Amount	The ratio of the total amount of loans the lead arranger has made to the borrower in the last five years to the total amount of loans taken by the firm during the same period
Top 3 Arranger	A dummy variable: one if at least one of the lead arrangers of the syndicated loan is among the top 3 percentile in terms of market share in the syndicated-loan market
Top 10 Arranger	A dummy variable: one if at least one of the lead arrangers of the syndicated loan is among the top 10 percentile in terms of market share in the syndicated-loan market
Arranger Size	The natural logarithm of the lead arranger's total assets
Small Arranger	A dummy variable: one for lead arrangers with total assets below the sample median
ln(*Loan Amount*)	The natural logarithm of the loan facility amount in millions of dollars
ln(*Loan Maturity*)	The natural logarithm of the number of months from the facility start date to the facility end date
Term Loan	A dummy variable: one if the loan type is term loan
Revolver	A dummy variable: one if the loan type is revolver
364-day facility	A dummy variable: one if the loan type is 360-day facility
Corporate Purpose	A dummy variable: one if the loan purpose is for corporate
Working Capital	A dummy variable: one if the loan purpose is for working capital
Takeover	A dummy variable: one if the loan purpose is for takeover
Debt Repayment	A dummy variable: one if the loan purpose is for debt repayment
Covenant	A dummy variable: one if there exists at least one covenant in the loan contract
P.Covenant	A dummy variable: one if there exists at least one performance covenant in the loan contract
Opacity	A dummy variable: one for firms without Standard and Poor's long-term issuer rating
Firm Reputation	The natural logarithm of the number of times that the firm has borrowed in the syndicated-loan market during the last five years
Firm Size	The natural logarithm of the firm's total sales at close
Small Firm	A dummy variable: one for firms that have total sales below the sample median at close

(Continued on next page)

Table 21. Variable Definitions (Continued)

Variable	Definition
Profitability	The ratio of earnings before interest, taxes, depreciation and amortization to the book value of total assets
Tangibility	The ratio of plant, property and equipment to total assets
Leverage	The ratio of total debt (i.e., the sum of debt in current liability and long-term debt) to book value of total assets
Financial Distress	A dummy variable: one for firms with Altman (1968) Z-Score below 1.81
Distance	The spherical distance measured in kilometers between the borrowing firm's headquarters and the headquarters of the lead arranger of a syndicated loan

Essay Three

4

Does Collateral Reduce Loan-Size Credit Rationing? Survey Evidence

With Jens Forssbæck

1 Introduction

Access to credit is a major concern, particularly for small firms. How important is collateral for securing access to credit for small businesses? The predominant view in the financial intermediation literature is that (equilibrium) rationing in credit markets arises primarily as a consequence of information asymmetries between lender and borrower (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981), and that the provision of collateral by borrowers can work as a signaling or commitment device that addresses the information problems that are the source of credit rationing (Bester, 1985, 1987; Besanko and Thakor, 1987; Chan and Thakor, 1987).[1] Consequently, collateral should reduce credit rationing. Less clear, however, is whether collateral plays an independent role in the presence of alternative mechanisms to overcome informational asymmetries that may substitute for or complement collateral (such as lending relationships, screening/monitoring, or contractual devices other than collateral), and the importance of this role. Despite the strong dependence of small firms on bank credit (**?**Black and Strahan, 2002), their greater information problems, and the wide use of collateral in small business lending (Leeth and Scott, 1989; Cowling, 1999; Berger et al., 2011a), empirical evidence on the link between collateral and rationing remains scarce and essentially only indirect. The empirical literature is also mixed on exactly why collateral is used and by which firms.[2]

The paucity of direct empirical evidence on the relationship between collateral and credit rationing may in large part be due to observability and estimation difficulties. First, the relationship between collateral and credit rationing is virtually impossible to test meaningfully for loan-level data (at least using single-equation specifications). In the case of full "quantity rationing", where a loan applicant is denied credit altogether (also known as borrower rationing), collateral is unobservable simply because no loan transaction ever takes place. In other words, collateral is only observed if there is a loan, which by definition precludes quantity credit rationing. A few recent empirical contributions (Becchetti et al., 2011; Kirschenmann, 2016) have addressed this issue by focusing on "loan size rationing" (Schreft and Villamil, 1992; Kjenstad et al., 2002), where the loan amount granted is lower than the amount applied for (also referred to as loan amount rationing, and directly interpretable as excess demand at the individual borrower level). However, the relative amount granted is only observed if the loan application was not

1 For a review of theoretical contributions on collateral as a device to reduce information asymmetries, see Coco (2000).

2 For a survey focusing on recent empirical evidence on the determinants of collateral (with implications for credit rationing), see Steijvers and Voordeckers (2009). At a general level, Haselman et al. (2010) find that discrete changes in collateral law are more important than bankruptcy creditor rights for credit supply.

turned down completely. It also requires that the prospective borrower had a credit demand to begin with, and made an application. All these prior outcomes may be influenced by factors that also determine loan amount rationing, suggesting that estimation of this type of rationing necessarily implies working with a non-random sample, with selection bias as the likely consequence.

A second problem related to estimation is that even if one disregards the process whereby a loan came to be approved, loan contracting terms are simultaneously determined (Brick and Palia, 2007). This co-determination may include, for instance, the relative loan amount granted (rationing), the loan interest rate, as well as any collateral requirements. Another way to frame this problem is to note that under the maintained hypothesis that collateral addresses the information problems that are at the root of credit rationing, the extent to which such problems are present jointly determines both collateral use and rationing. The same argument may extend also to observable firm characteristics – whether they are proxies of information availability (such as firm age, size, or the length or scope of the lender-borrower relationship) or other characteristics, such as credit risk, that are believed to influence both collateral and rationing. Thus, even after accounting for non-random selection of the observed sample, endogeneity concerns remain.

The aim of this paper is to test the direct relationship between collateral provision and credit rationing. We use survey data drawn from the 1993, the 1998 and the 2003 versions of the Survey of Small Business Finances (SSBF), conducted by the Federal Reserve Board, which provides us with a total of 11,503 firm-level observations with detailed responses regarding the respondent firms' recent credit application experiences.[3] We focus on loan size rationing (whether the

3 Survey data has been rather extensively used in the literature, particularly in studies focusing on the determinants of collateral (but also, to some extent, to study credit constraints). To name a few, see, e.g., Chakraborty and Hu (2006); Brick and Palia (2007); Chakravarty and Yilmazer (2009) for studies using the SSBF, and Harhoff and Körting (1998); Lehmann and Neuberger (2001); Cenni et al. (2015) for studies using non-U.S. surveys. A number of other studies use actual loan application data, e.g., Jiménez et al. (2006); Puri et al. (2011); Jiménez et al. (2012).

borrower was granted the full amount applied for) in the final loan level estimations, so that there is variation in rationing for the approved loans for which we can observe collateral, but the data allow us to model the entire loan application and approval process.

To address the above-mentioned selection and endogeneity issues, our estimation is done in two parts. The first part is a three-step sequential selection process, where we use a trivariate probit model to jointly estimate three conditional sequential equations: first, firms' credit demand; second, firms' propensity to apply for a loan (conditional on credit demand); and third, the likelihood of loan approval (given a firm's credit demand and application decision). The second part estimates the effect of collateral on loan size credit rationing, allowing for endogenously determined collateral and loan interest rates, and accounting for selection bias arising from the loan application process estimated in the first part.

The trivariate probit selection model shows that demand for credit, the firm's decision whether to apply for a loan, and the lender's decision whether to approve the application are a sequence of strongly interrelated outcomes, suggesting that the estimate of the effect of collateral on loan size rationing is likely to be biased if non-random selection is left unaccounted for. In fact, when we ignore selectivity issues and treat collateral and interest rates as exogenous in a set of benchmark regressions, we find little evidence of an effect of collateral on rationing. In contrast, when we control for these potential biases, we find results that are robust both to different proxies of collateral and to alternative estimation methods. The results show that collateral not only reduces the likelihood of experiencing loan size rationing, but also reduces the proportion of the loan amount rationed.

The rest of the paper is structured as follows. The next section gives a brief review of theoretical and empirical literature on credit rationing and collateral, Section III describes the methodology and estimation framework, and Section IV provides a detailed description of the data and variable definitions. We present our results in Section V, and Section VI, finally, concludes.

The theoretical literature provides several explanations for credit rationing and how collateral might mitigate it. Early theories rely on exogenous restrictions on interest rates (either *ad hoc* assumptions of price rigidity, or institutional constraints, such as usury laws) to explain the occurrence of quantity rationing in the credit market. The implication is that for certain prospective borrowers, there may be no interest rate that a lender is able or allowed to charge at which its expected return is positive (Freimer and Gordon, 1965; Jaffee and Modigliani, 1969).

The more contemporary view relies on lenders' inability to perfectly observe borrowers' repayment capability, which prevents them from charging interest rates that are sufficiently differentiated to reflect borrower heterogeneity. In this setting, raising the loan rate adversely affects lenders' credit portfolios via sorting and incentive effects: first, average loan quality is reduced, because at a higher interest rate, high-risk borrowers are more likely to self-select into the applicant pool; second, less profits accrue to the borrower, which may induce lower effort levels and/or risk-shifting behavior (Stiglitz and Weiss, 1981, 1987). Consequently, lenders' expected return does not rise monotonically in the interest rate charged due to adverse selection and moral hazard, which may result in a pooling equilibrium loan rate below the market-clearing level that generates excess demand for credit. Some prospective borrowers may then be rationed despite being observationally indistinguishable from borrowers that are approved for a loan, and despite being willing to pay a higher interest rate.

A sizable theoretical literature suggests that collateral provision may mitigate credit rationing by reducing the *ex ante* and/or *ex post* effects of borrower-lender information asymmetries. Since the provision of collateral entails the risk of losing the pledged assets, borrowers with a lower probability of ending up in default states are more likely to pledge collateral, which suggests that low-risk borrowers use collateral to signal repayment capability to the lender (Bester, 1985; Chan and Kanatas, 1985; Besanko and Thakor, 1987). Thus, collateral reduces adverse selection, and should ultimately mitigate credit rationing. Collateral may also serve as an incentive device to prevent moral hazard by discouraging borrowers from switching to riskier investment projects (Bester, 1987; Chan and Thakor, 1987; Boot et al., 1991), by encouraging borrowers to choose a high effort level (Watson, 1984; Innes, 1990), and by deterring strategic default by enforcing loan repayment (Benjamin, 1978; Hess, 1984; Beutler and Grobéty, 2013). Alternative theories suggest collateral as a substitute (rather than a complement) to screening – the "lazy banks" hypothesis (Manove et al., 2001) – or as an instrument to increase the credit decision efficiency of small relationship lenders in the face of competition from arms' length lenders (Inderst and Müller, 2007).

The results of the empirical literature on credit rationing – particularly in terms of pinning down information asymmetries as a primary driver of rationing – are somewhat mixed. The early empirical literature is limited by having to rely on indirect or inferential measurement of rationing for observability reasons made clear above. Specifically, the implication of credit rationing theory that loan rates are rigid, or sticky with respect to base interest rates, has been used. The testing approach of Berger and Udell (1992) focuses on inferring rationing from rigidities in loan pricing (while recognizing that sticky loan pricing is consistent with, but not sufficient evidence of, rationing). They find that rates on loans issued under commitment are essentially as sticky as those on non-commitment loans, which is inconsistent with interpreting loan rate stickiness as a sign of credit rationing (since commitment loans by definition cannot be rationed). In addition, since commitment loans should be less subject to information problems, loan rate stickiness appears largely unrelated to information asymmetries. The results of Berger and Udell (1992) have later been shown to hold for UK data (Cowling, 2010).

Jappelli (1990) appears to have been the first to use survey data to identify constrained ("rationed") borrowers, but studies constrained *consumers*. Levenson and Willard (2000) use survey data (SSBF) to estimate the probability of loan denial (conditional on applying) for *firms*. They find that rationed firms are more likely to be smaller and younger, and owned by the original founder, but conclude rationing to be a minor phenomenon, as do Berger and Udell (1992). Han et al. (2009) likewise use the SSBF to study "self-rationing" (the probability of not applying for a loan for fear of rejection), and find that riskier borrowers in more concentrated markets are more likely to self-ration. Methodologically closer to our paper is the study by Chakravarty and Yilmazer (2009). They focus primarily on the effect of lender-borrower relationships on the loan rate, but in the process find that firm size and age are negatively associated with self-rationing as well as with loan denial, whereas firm risk is positively associated with rationing outcomes. Drakos and Giannakopoulos (2011), testing loan denial conditional on demand and using survey data from Eastern Europe, find a negative effect of firm size (but no effect of firm age or risk). Cenni et al. (2015), using Italian survey data, find only weak evidence of a relationship effect, but otherwise little that suggests an information-asymmetry effect on rationing.

Two recent studies use actual loan application data to study loan size rationing. Becchetti et al. (2011) and Kirschenmann (2016) both find negative effects of firm size and lender-borrower relationships on loan size rationing. Kirschenmann (2016) further finds that rationing decreases as relationships deepen over time, as well as a mixed impact of collateral on credit rationing. A number of other recent papers also use actual loan application data, but focus on supply-side effects on loan denials. Puri et al. (2011) study the effects of aggregate credit shocks on retail lending and find that banks that are more affected by the shock are more likely to ration credit to their loan customers, but also that rationing occurs across the entire spectrum of borrower risk with very little migration to "quality" borrowers. In a similar vein, Jiménez et al. (2012) find strong positive effects of lender banks' capital and liquidity ratios and profitability on the probability of granting a loan to otherwise comparable borrowers, which appears inconsistent with the notion that rationing occurs primarily (or at least only) as a consequence of borrower characteristics.

A methodologically different approach is the use of disequilibrium models to study credit rationing. Existing studies in this vein reach conflicting results when it comes to the effect of collateral: whereas Ogawa and Suzuki (2000) and Atanasova and Wilson (2004) suggest that collateral increases loan supply, using borrowers' land assets and total assets, respectively, as proxies for collateral, Shen (2002) suggests it does not. Carbo-Valverde et al. (2015) use a disequilibrium approach to study the effect of securitization on credit rationing, and find that lenders' reliance on securitization reduces rationing under normal periods, but some types of securitized assets aggravate borrowers' credit constraints in crisis periods, i.e., they find further evidence of supply-side effects on credit rationing.

The existing evidence on the determinants of collateral is likewise mixed, and evidence of the role of information asymmetries relies, again, on indirect proxies. In addition, evidence that collateral reduces information asymmetries gives only indirect evidence on the role of collateral for credit rationing. A main concern in the literature is the question whether collateral primarily solves adverse selection problems (which is typically taken to imply a negative relationship between firm risk and collateral, since collateral then works as a quality signaling device), or if it is primarily a disciplining mechanism to prevent moral hazard (a positive relationship between firm risk and collateral is assumed). Although theoretically, both adverse selection and moral hazard contribute to credit rationing, whether one or the other is more important may play out on the expected effect of collateral on credit rationing, because if the moral hazard motivation dominates but collateral imperfectly compensates for borrower risk, then loans that are more likely to be collateralized are also more likely to be rationed. For example, Berger and Udell (1992) find (indirect) evidence of somewhat higher rationing for collateralized loans, and interpret the finding in terms of borrower information problems that are not fully resolved by collateral. If, on the other hand, high quality borrowers use collateral as a signal to overcome adverse selection, then collateralized loans should be *less* subject to rationing.[4]

4 It can be noted that lower *observable* risk of borrowers that were granted a loan is not necessarily a good proxy of unobserved borrower quality, particularly if high-quality borrowers opt out of the applicant pool due to adverse selection and/or low-quality borrowers are denied loans altogether; in turn, higher risk does not necessarily proxy for moral hazard: a borrower can have high *ex ante* observed credit risk, but have a high-quality project and not be prone to shirking or risk-shifting.

A large number of studies directly test the determinants of collateral. Many of these use survey data (Leeth and Scott, 1989; Avery et al., 1998; Harhoff and Körting, 1998; Cowling, 1999; Hernández-Cánovas and Martínez-Solano, 2006), most test the incidence of collateral as a binary outcome, but a number of studies also test determinants of the *amount* of collateral (Machauer and Weber, 1998; Lehmann and Neuberger, 2001; Menkhoff et al., 2006; Jiménez et al., 2006). With few exceptions – Brick and Palia (2007) is one – empirical studies on the determinants of collateral do not account for the simultaneous determination of different price and non-price loan contract features (such as loan interest rate and collateral), suggesting results should be interpreted primarily as correlations. A limited number of more recent studies (partially) account for incidental truncation (Chakraborty and Hu, 2006).

Although evidence overall is mixed, when it comes to basic firm characteristics, one result appears universally consistent: firm age is negatively associated with collateral use. The conventional argument is that, unlike startups and young businesses, older firms have track records, tractable credit histories, etc. (Berger and Udell, 1995) – in short, are less subject to information problems. Similar consistency does not appear for other basic firm characteristics, such as firm size, which alternately take on positive (Berger and Udell, 1995; Chakraborty and Hu, 2006) and negative (Degryse and Cayseele, 2000; Lehmann and Neuberger, 2001) associations with collateral, or firm credit risk, which is equally sometimes estimated to have a positive (Machauer and Weber, 1998; Jiménez et al., 2006) and sometimes a negative (Lehmann and Neuberger, 2001) relationship with collateral. Several studies also find significant effects of firm type (legal or incorporation status) and/or industry. Evidence on the latter may be interpreted as somewhat consistent with the notion that firms in industries with a high share of tangible assets (such as real estate, manufacturing, or retail trade) are more likely to have collateralized loans (Leeth and Scott, 1989; Berger and Udell, 1995; Avery et al., 1998; Harhoff and Körting, 1998). Results on the relationship between collateral and other loan terms are, again, mixed. Whereas collateral appears to be relatively consistently more likely for larger loan amounts (Leeth and Scott, 1989; Degryse and Cayseele, 2000; Jiménez et al., 2006; Berger et al., 2011a), it is associated with higher loan rates in some studies (Berger and Udell, 1990, 1992; Brick and Palia, 2007) and with lower rates in others (Machauer and Weber, 1998; Degryse and Cayseele, 2000; Chakravarty and Yilmazer, 2009). The relationship with maturity is similarly indeterminate (Leeth and Scott, 1989; Harhoff and Körting, 1998; Degryse and Cayseele, 2000).

A major concern in the empirical literature is also the effect of lender-borrower relationships (Petersen and Rajan, 1994) on collateral use. Relationships and collateral are considered primarily as substitutes, i.e., alternative mechanisms to overcome pre-contractual information asymmetries. Importantly, however the duration and scope of prior lender-borrower relationships are unlikely to be endogenous with respect to collateral, since they are – by definition – pre-existing when the loan is contracted. The effect of relationships on collateral appears ambiguous. On the one hand, borrowing from a main bank, or house bank, increases the incidence of collateral, and long-term exclusive relationships with a single bank can also increase collateral or personal commitment requirements (Lehmann and Neuberger, 2001; Menkhoff et al., 2006; Voordeckers and Steijvers, 2006). This could be the result of the "holdup problem" – banks extract rents from firms that are captive with a single lender. On the other hand, there is consistent evidence that the length of prior relationship between lender and borrower decreases the incidence of collateral, which would tend to point in favor of a conventional information-asymmetry story (Berger and Udell, 1995; Chakraborty and Hu, 2006; Jiménez et al., 2006; Brick and Palia, 2007). Another commonly used indicator is the number of bank relationships maintained by the borrower firm, which is found to be positively associated with collateral use in some studies (Harhoff and Körting, 1998; Chakraborty and Hu, 2006), whereas others find the association to be negative or inconclusive (Menkhoff et al., 2006; Jiménez et al., 2006). The effect of relationships could therefore also depend on competition between lenders. The direct effect of competition (typically measured by bank market concentration) on collateral use is, again, inconclusive – for instance, the results of Jiménez et al. (2006) and Voordeckers and Steijvers (2006) point in different directions.

A smaller number of studies use more direct identification strategies to isolate the effect of *ex ante* information availability on credit rationing or on collateral use. Cheng and Degryse (2010) study the effect of information sharing via a public credit registry on the approval of consumer credit card applications by a Chinese bank. They find that information sharing does not affect credit rationing on average, but that sharing of positive information by other banks results in customers receiving higher credit card lines. Berger et al. (2011a) exploit a shift in lenders' access to information about borrowers provided by the adoption of a new credit scoring technology in loan underwriting to investigate whether this reduction in *ex ante* information asymmetry reduces the incidence of collateral, and find that this is the case. Finally, exploiting a legal change that reduced the value of company mortgages (a widely used form of collateral for businesses) in Sweden, and comprehensive data from a single bank, Cerqueiro et al. (2016) find that the bank in response to this exogenous shock to collateral values significantly reduced its internal credit limits to borrowers with collateralized business loans.[5]

To sum up, although the information-asymmetry paradigm dominates the theoretical literature on credit rationing and collateral, the empirical literature does not provide conclusive evidence in support of this view (at the very least, it suggests some additional mechanisms). There is evidence of a role for information asymmetries in both credit rationing and collateral provision, but there are also several open issues and some results that appear to challenge the predominant view. In particular, there is substantial evidence of supply-side effects on rationing, and the effect of observable borrower risk (and possibly other firm characteristics) for collateral use remains unclear, particularly in the presence of competing mechanisms for reducing borrowers' *ex ante* information advantage. There appears to be industry effects, and collateral may mostly be used in indus-

5 Note that this effect is conditional on there already being a collateralized loan in place.

tries where information asymmetries are low and tangible assets are high. If collateral works as insurance (rather than as a signaling device), then borrower characteristics may be more important for non-collateralized loans. In that sense, collateral may compensate for (bad) borrower characteristics, and we may not expect a negative effect of collateral on rationing. It may also be the case that for collateralized loans, the value of the collateral is more important than borrower characteristics, possibly suggesting that if credit rationing is influenced by supply-side factors and overall economic conditions or shocks that negatively affect collateral values, then collateralized loans may be more exposed to rationing than non-collateralized loans. For instance, the results of Puri et al. (2011) indicate that mortgage loans are more rationed than (presumably less frequently collateralized) consumer loans as the result of a shock.

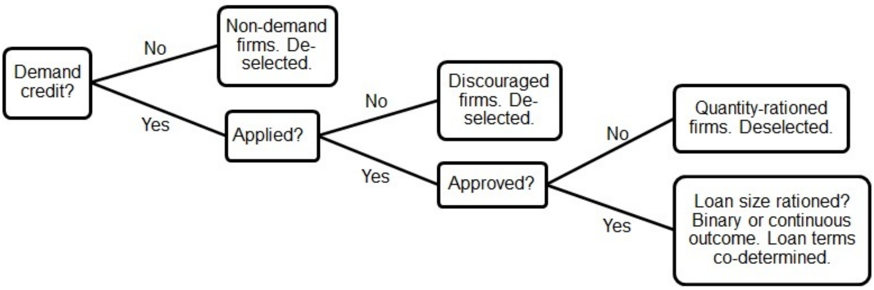
3 METHODOLOGY

Estimation of the direct relationship between collateral and credit rationing introduces a number of econometric challenges. Our end goal is to estimate the determinants of credit rationing. We define firms as credit rationed if we observe that they have unsatisfied demand for credit. Specifically, we focus on loan size rationing (the loan amount granted is lower than the amount applied for) – first, because this provides a clean and intuitive measure of excess demand at the individual borrower level; second, because this is the only possible definition that allows us with certainty to observe other loan terms (including collateral). But firms can only be loan-size-rationed if they are not denied credit altogether, and it is likely that the probability of being loan-size-rationed is determined largely by the same factors that determine loan approval/denial.

Moreover, there may be factors influencing a firm's chances of being approved for a loan that are also related to the likelihood that the firm had a credit demand to begin with, and made a loan application. In particular, loan approval and firms' expectation of loan approval (and therefore their propensity to apply) may depend on the *availabil-*

ity of collateral. Thus, the sub-sample of firms for which we can observe the extent of loan size rationing is not a random draw from the full sample, which renders estimation of any single-equation model of credit rationing inappropriate. The non-randomness of the process by which size-rationed loans and loan terms come to be observed is likely to result in biased estimates. In addition, economic reasoning and prior evidence suggest that for loans that are approved, the loan contract terms – including the loan amount as a proportion of the amount applied for – are simultaneously determined, because they are the joint outcome of a bargaining process, and the "package" of loan terms may be driven by common observable and/or unobservable borrower characteristics. To address these issues, we adopt a sequential estimation approach consisting of two main parts. The basic sequence is summarized in Figure 1.[6]

Figure 1
Sequential estimation procedure



The first part is a three-step selection process, modeling how firms end up with an approved loan with observable loan terms. From the total (randomly assigned) sample at our disposal, we first observe whether a firm made a loan application or not. Firms that made a

6 The sequence is essentially determined by the design of the SSBF surveys, and similar to the sequential structure in, e.g., Cole and Sokolyk (2016).

loan application have a manifest loan demand. But there are also firms that do not apply for credit even though they need it. This group of firms are called "discouraged” borrowers (Jappelli, 1990; Kon and Storey, 2003; Han et al., 2009). The survey data allows us to identify this group of firms, which are included among the firms with non-zero credit demand. In latent-variable notation, the first step in the selection process is then:

$$Demand_i^* = \alpha_1 + \beta_{F1}' X_{F,i} + \beta_{G1}' X_{G,i} + \gamma_1' Z_{1,i} + \epsilon_{1,i} \quad (14)$$

where the observable counterpart of the latent variables $Demand_i^*$ is the indicator $Demand_i$, which takes on unit value if firm i either applied for a loan or is identified as a discouraged borrower, X_F is a vector of core firm characteristics, X_G is a set of general control variables (which includes dummies for geographical region and survey release), and Z_1 is a set of indicators constructed from responses to survey questions specifically reflecting the firm's financing situation (detailed variable descriptions are deferred to Section IV).

Equation 1 is estimated for the full sample of firms. The next step in the selection process estimates the probability that a firm applies for a loan (conditional on demand):

$$Applied_i^* = \alpha_2 + \beta_{F2}' X_{F,i} + \beta_{O2}' X_{O,i} + \beta_{G2}' X_{G,i} + \gamma_2' Z_{2,i} + \epsilon_{2,i} \quad (15)$$

where the propensity to apply is proxied by the indicator $Applied_i$, which is equal to one if firm i applied for a loan and zero if i was discouraged from applying. $Applied_i$ is only observed if $Demand_i = 1$, and missing otherwise. X_O is a vector of firm owner characteristics believed to influence discouragement (including, e.g., demographic information and credit history), Z_2 is a set of variables related to alternative sources of credit. The final step in the selection process determines if, conditional on loan demand and application, a firm will be granted *some* loan amount (and therefore will be observed in the sub-sample for which loan terms are available):

$$\begin{aligned} Approved_i^* = \alpha_3 + \beta'_{F3}X_{F,i} + \beta'_{O3}X_{O,i} + \beta'_{H3}X_{H,i} \\ + \beta'_{G3}X_{G,i} + \gamma'_3 Z_{3,i} + \epsilon_{3,i} \end{aligned} \tag{16}$$

where the latent approval rate is denoted by the indicator $Approved_i$, which is equal to one if i was approved for a loan, equals zero if i was rejected completely, and is observed only if $Applied_i = 1$. Because all firms that are included in this last step made a loan application, we can observe some loan characteristics (but not all loan terms, since some applications were rejected), and these make up the vector X_H. Z_3 is a set of additional variables influencing loan approval probability.

The selection process is estimated as a trivariate probit with sample truncation, assuming correlated and jointly normally distributed errors, using a full-information maximum likelihood conditional mixed process procedure, where the trivariate cumulative normal distribution is simulated using the Geweke-Hajivassiliou-Keane (GHK) algorithm, see Roodman (2011) for details. Accounting for the selection procedure as described above ensures that the relationship between loan size rationing and loan contract terms that we analyze in the second part of the estimation procedure reflects lenders' decision to restrict the availability of credit and is not biased by non-random sampling effects related to borrowers' demand or likelihood to apply and be approved for credit. We follow the conventional Heckman two-step approach to account for selectivity and calculate the inverse Mills ratios from the selection equations, which are then included as regressors in the second part of the estimation.

The estimation in the second part is based on an implicit three-equation simultaneous-equations system, where the endogenous variables are a measure of loan size rationing, a variable indicating collateral, and the loan interest rate. We do not specify the full structure of the system, but focus on the main equation of interest:

$$\begin{aligned} Credit\ rationing_i = \alpha_4 + \beta'_{F4}X_{F,i} + \beta'_{O4}X_{O,i} + \beta'_{L4}X_{L,i} + \beta'_{G4}X_{G,i} \\ + \theta_C \widehat{Coll}_i + \theta_S \widehat{Intr}_i + \Pi'_4 M_i + \epsilon_{4,i} \end{aligned} \tag{17}$$

with predictions of collateral and loan rates estimated from reduced-form equations and defined as:

$$\widehat{Coll}_i = \hat{\alpha}_5 + \hat{\beta}'_{F5} X_{F,i} + \hat{\beta}'_{O5} X_{O,i} + \hat{\beta}'_{L5} X_{L,i} + \hat{\beta}'_{G5} X_{G,i} + \eta \hat{\Pi}'_5 M_i + \hat{\gamma}'_5 Z_{CS,i} \quad (18)$$

and

$$\widehat{Intr}_i = \hat{\alpha}_6 + \hat{\beta}'_{F6} X_{F,i} + \hat{\beta}'_{O6} X_{O,i} + \hat{\beta}'_{L6} X_{L,i} + \hat{\beta}'_{G6} X_{G,i} + \eta \hat{\Pi}'_6 M_i + \hat{\gamma}_6 Z_{CS,i} \quad (19)$$

where *Credit rationing* is loan size rationing (measured as an indicator or a continuous variable), *Coll* is collateral, *Intr* is the loan interest rate, X_L is the full set of observed loan characteristics (which subsumes X_H from equation 3), M is the vector of inverse Mills ratios from equations 1, 2 and 3, and Z_{CS} are instruments for the loan terms.

This second part of the estimation is initially carried out using linear probability models estimated by IV-GMM although both loan size rationing and collateral are in some estimations observed as binary variables – primarily to facilitate identification testing and to ensure that identification is not based on functional form. In the final regressions, however, we estimate equation 4 using IV-probit or IV-tobit, depending on the definition of the dependent variable.

A potential critique is that we split up credit rationing into one discrete approval/denial decision, and one decision determining the relative loan amount granted, when these outcomes might, perhaps, be more appropriately seen as different points on a single scale. The relative loan amount granted is a clean measure of rationing because it captures the difference between credit demanded and credit supplied for each prospective borrower. But ideally, this should really also include completely denied borrowers, because for these borrowers the relative amount granted is simply equal to zero. However, for completely denied borrowers, loan contract terms are not observable, so estimating rationing as a single potential outcome in the closed interval [0,1] would necessarily imply having to drop other loan terms as potential explanatory variables. We do the second-best thing, and control for the selection bias inherent in testing only loans that were (partially or fully) granted.

4 DATA

4.1 *The Survey of Small Business Finances*

The data employed in this paper are the 1993, the 1998 and the 2003 releases of the Survey of Small Business Finances (SSBF)[7] – the three most recent in four rounds of surveys conducted by the Federal Reserve at approximately five-year intervals between 1987 and 2003. The surveys cover nationally representative samples of small businesses operating in the U.S. at the end of each survey year, with survey responses collected over approximately three-year periods prior to each release year. Small businesses are defined as firms with less than 500 employees, and the firms covered in the surveys are non-farm enterprises. The surveys provide information about basic characteristics of the firms, including firm age, organizational form, standard industrial classification, and a considerable amount of information on the firms' owner(s). Selected financial-statement data and information on credit history are also covered by the survey.

In addition to firm and owner characteristics, the SSBF also provides information on the most recent borrowing experiences of each firm. The survey data cover information on whether the firm applied for credit, and whether the application was approved or rejected. If the lender extended credit, the survey provides information on the terms of the loan, including interest rate, loan amount and collateral. Importantly, it also covers information on loan applications that were rejected, including type of loan and main reasons that the loan application was rejected, which is the main advantage of the survey data

7 The SSBF datasets are publicly available and can be downloaded at the Federal Reserve's website `http://www.federalreserve.gov/pubs/oss/oss3/nssbftoc.htm`.

that allows us to control for the sample truncation inherent in studying only loans that are approved. In addition, the surveys provide some (though only very rudimentary) information about the lenders to which the firms applied for loans, and relatively detailed documentation about prior relationships between lender and borrower.

Our analysis pools the observations from the three SSBF releases into one dataset. The total number of firms covered in the surveys is 4,637 (1993), 3,561 (1998) and 4,240 (2003). Besides making the dataset larger, an additional reason for pooling observations across the surveys is that it makes results less sensitive to possible time-specificity and business cycle effects. The three rounds of SSBF, however, differ somewhat from each other with respect to some questions aimed at collecting information on characteristics of firms and their owners. This has implications for the variables we use in that only those variables that the three surveys have in common are included in the analysis.

We apply the following data filtering procedures. First, we limit the sample to non-financial firms by dropping firms from the financial industry (1-digit SIC code equal to 6), following previous empirical literature. Some firms report negative values for total sales; we exclude these observations from the sample. We also exclude firms with approved loan applications that report zero values for loan maturity or loan interest rate. After these restrictions, our final sample contains 11,503 observations.

4.2 *Loan Demand, Loan Applications, and Credit Rationing*

The section of the 1993 and the 2003 surveys that covers the firms' most recent borrowing experiences includes both new applications for lines of credit and other types of loans and *renewals* of existing lines of credit, whereas the 1998 survey only covers information on applications for new loans. Because we pool the three surveys into one dataset, our analysis focuses on new loan applications only. Applications for credit cards, trade credit with suppliers, or applications that were withdrawn or still pending when the surveys were conducted are not included.

Excluding renewals of existing lines of credit, the firms were asked “How many times in the last three years did the firm apply for new loans?”. Based on the response to this question, we construct the binary variable $Applied_i$ to identify firms ($i = 1, ..., N$) that applied for one or more new loans:

$$Applied_i = \begin{cases} 1 & \text{if single} \vee \text{multiple new loans} \\ 0 & \text{otherwise.} \end{cases} \tag{20}$$

$Applied_i = 0$ includes discouraged borrowers, but these firms need to be distinguished from other non-applicants because they have a credit demand. The dataset allows us to make this distinction. If a firm’s response to the question "During the last three years, were there times when [FIRM] needed credit, but did not apply because it thought the application would be turned down?” is YES, we identify the firm as a discouraged borrower:[8]

$$Discouraged_i = \begin{cases} 1 & \text{if } Applied_i = 0 \wedge \text{fear rejection} \\ 0 & \text{otherwise.} \end{cases} \tag{21}$$

Based on the responses to the questions on loan applications and fear of rejection, we are able to distinguish between firms with and those without a credit demand. Thus, we define the binary variable $Demand_i$ as:

$$Demand_i = \begin{cases} 1 & \text{if } Applied_i = 1 \vee Discouraged_i = 1 \\ 0 & \text{otherwise.} \end{cases} \tag{22}$$

$Demand_i$ is observed for the full sample of firms, and is the dependent variable in the first step of the selection process (equation 1).

8 Like Chakravarty and Yilmazer (2009), we only define firms as discouraged that *never* applied, but firms that answered YES to this question but still applied at least once are treated as though they were not discouraged. In contrast to Chakravarty and Yilmazer (2009), we account for how firms that did not apply but were not discouraged are deselected from the sample; i.e., we do not simply drop non-demand firms from the sample due to the potential selection bias discussed above.

$Applied_i$ is the dependent variable in equation 2, and is observed if $Demand_i = 1$ and missing otherwise.

Firms with nonzero loan applications in the last three years were also asked, regarding their most recent loan application, “Was this recent loan application approved or denied?”. Based on the response to this question, we define the last dependent variable in the selection process as:

$$Approved_i = \begin{cases} 1 & \text{if approved} \\ 0 & \text{otherwise.} \end{cases} \tag{23}$$

$Approved_i$ is observed if $Applied_i = 1$, and missing otherwise. Firms are defined as quantity-rationed if they made at least one loan application during the previous three years but were not approved for a loan. Among *approved* loan applications, the loan amount granted may be some fraction of the amount applied for. We identify these loans based on responses to the questions “What was the total dollar amount for which the firm applied?” and “What was the dollar amount of the credit granted?”. The first question refers to loan demand, the second refers to loan supply. Firms are defined as loan-size-rationed if the supplied loan amount ($Loan_i^s$) for the most recently approved loan is smaller than the demanded amount ($Loan_i^d$). In the analysis, we use the continuous variable $\textit{Proportion rationed}_i$ (i.e., proportion denied), defined as $1 - Loan_i^s / Loan_i^d$, as well as a binary variable indicating loan size rationing, and defined as:

$$\textit{Loan size rationing}_i = \begin{cases} 1 & \text{if } Approved_i = 1 \\ & \wedge\ Loan_i^s < Loan_i^d \\ 0 & \text{otherwise.} \end{cases} \tag{24}$$

4.3 *Collateral and Guarantees*

Collateral use for approved loans is defined from the firms’ response to the survey questions “Was any type of collateral required to secure this most recent loan?” and "Was the firm required to have a personal Guarantee, Cosigner, or other guarantor?”. A positive (yes) response to either of these questions gives unit value to the binary variable *Collateral*, which is consequently equal to zero for unsecured loans.

For collateralized loans, firms are asked the follow-up question "What collateral was used to secure this most recent loan?". Possible responses to this question fall within one or several of a total of seven categories of collateral.[9] Based on the answer to this question and on whether or not the loan was secured by a guarantee, we define the alternative measure *#collateral types*, which takes on integer values between 0 and 8, reflecting the number of different types of collateral (including any possible guarantee) that were used to secure a loan.

4.4 *Control Variables*

We control for several variables that may be systematically related to credit rationing, self-rationing and the determinants of collateral, and our choice of variables included at various stages in the loan application/approval decisions is based both on theoretical considerations and on previous empirical literature (discussed in Section 2). We are also constrained to using data extracted from the survey only: the surveyed firms are anonymized and cannot be matched to alternative data sources (the same holds true for the lenders).[10]

Firm Characteristics: Firm size is measured as (the natural logarithms of) both total sales and the total number of employees, since both revenues and the size of the employee force have proved to be associated with credit demand (Drakos and Giannakopoulos, 2011), self-rationing (Chakravarty and Yilmazer, 2009; Han et al., 2009), loan approval (Chakraborty and Hu, 2006; Chakravarty and Yilmazer, 2009; Drakos and Giannakopoulos, 2011; Carbo-Valverde et al., 2015), col-

9 The categories are: (1) inventory or accounts receivable, (2) business equipment or vehicles, (3) business securities or deposits, (4) business real estate, (5) personal real estate, (6) other personal assets, and (7) other collateral.

10 Control variables are included according to the point in the application process from which they become available. E.g., data on the lender from which they firm applied for a loan are only available for firms that made a loan application, and are included from equation **??** onward, etc.

lateral (Berger and Udell, 1995; Chakraborty and Hu, 2006), and the proportion of loan amount granted (Kirschenmann, 2016), and they are only modestly correlated. We prefer to use total sales rather than total assets, primarily due to the better distributional properties of the sales figures reported in the data. For instance, there is a substantial number of firms for which total assets take on very large negative values. For the same reason, we scale other firm-level financial variables by total sales.

Another firm characteristic that has been shown relevant for loan application (Chakravarty and Yilmazer, 2009), approval (Chakraborty and Hu, 2006; Chakravarty and Yilmazer, 2009; Jiménez et al., 2012; Carbo-Valverde et al., 2015) and the proportion granted (Kirschenmann, 2016) is firm age. Higher age may proxy better information availability (Diamond, 1989) and high reputational capital (Diamond, 1991). We measure firm age as the logarithm of the number of years the current owner has owned the business. Profitable firms are in a better position to use internally generated funds; hence they may need less external funding (Drakos and Giannakopoulos, 2011). Profitability has also proved to be significantly associated with loan approval (Drakos and Giannakopoulos, 2011; Jiménez et al., 2012). We use earnings scaled by total sales to control for firm profitability. We further include the ratio of total debt to equity to account for firm leverage, which has been related to credit need (Cenni et al., 2015), loan rate (Chakravarty and Yilmazer, 2009) and collateral (Berger and Udell, 1995). Both profitability and leverage are winsorized at the first and 99th percentiles to reduce the occurrence of outliers.

In the empirical literature, small business credit scores are commonly used to measure a firm's creditworthiness (Mester, 1997). However, credit scores are not available in the 1993 SSBF dataset, and we instead use the data on firms' credit histories reported in the surveys (Chakraborty and Hu, 2006; Brick and Palia, 2007; Jiménez et al., 2006; Chakravarty and Yilmazer, 2009; Cole and Mehran, 2011). In particular, we construct a dummy variable that takes the value one if in the past seven years the firm has declared bankruptcy, or if the firm in the past three years has had any business obligations past due for 60 days or more, and zero otherwise. The dummy variable *Low di-*

versification proxies the geographical scope of the business, and takes on unit value if the firm primarily does business in the area where its headquarters are located, and zero otherwise. Finally, variables related to firm characteristics also include dummies for legal incorporation type (C-corporation, S-corporation, partnership, or proprietorship) and industry (1-digit SIC codes).

Owner Characteristics: For small businesses, firm owner characteristics may influence both the propensity to apply for a loan and the likelihood of being approved. One such characteristic is owner education, which naturally lends itself to an interpretation in terms of human capital. We measure education as the dummy variable *College*, which takes on unit value if the data reports the main owner's education level as "college degree" or "post graduate degree", and zero otherwise.[11] We also include the length of the owner's business experience, defined as (the logarithm of one plus) the number of years the owner has worked managing or owning the business. We also include the logarithm of owner age. For firms with multiple owners, age and experience are the weighted averages of the owners.

Though results are somewhat mixed, a number of studies have found that belonging to a minority group can be detrimental to credit access (Gabriel and Rosenthal, 1991; Munnell et al., 1996; Coleman, 2002; Cavalluzzo et al., 2002; Blanchflower et al., 2003; Cavalluzzo and Wolken, 2005). To account for possible discrimination, we include the dummy variable *AfrAm ownership*, which is set to unity if more than 50 percent of the firm is African American owned, and zero otherwise. Similar dummy variables are also included for Asian and Hispanic owners. We also include the dummy variable *Female ownership*, to account for a possible gender effect (Carter et al., 2007). In addition, for small business financing, some studies suggest that there exists little separation between the firm's and the owner's credit risk (Ang et al., 1995). We therefore include a dummy variable that

11 The SSBF codes the level of owner education on a seven-step scale: "less than a high school degree", "high school graduate", "some college but no degree granted", "associate degree", "trade school/vocational program", "college degree", and "post graduate degree".

takes the value one if the business owner has declared bankruptcy in the past seven years, or if the owner has any obligation past due for 60 days or more in the past three years, and zero otherwise. Finally, we control for ownership concentration, measured as the percentage ownership share of the primary owner.

Relationship Characteristics: We include several measures of firm-lender relationships. The first is *Relationship length*, which is calculated as (the log of one plus) the number of years the borrowing firm has conducted business with the lender, and accounts for the strength (duration) of the lending relationship. We also include the *Number of sources* of financial services used by the firm. Lenders may offer multiple financial services as a way to "capture" the firm and build relationships (Boot, 2000). Evidence also suggests that non-credit financial services such as checking and saving accounts help the lender to better monitor different aspects of the firm's business (Mester et al., 2001). An additional relationship measure included is *Distance*, which equals one plus the log of the geographic distance in miles between the firm's and the lender's headquarters, as geographical proximity facilitates the collection and processing of soft information (Berger et al., 2005). We also make use of survey responses to the question "What factors influenced the firm's decision to apply for credit from [institution that approved]?" by including the dummy variable *Referral*, which takes on the value 1 if the reason is "Seller referral" and/or "Other referral", and 0 otherwise. Finally, we set the dummy variable *Previous loan* to unity if the response to the above equation is "Previous loan", and 0 otherwise.

Lender Characteristics: For firms that made at least one loan application, we observe the type of financial institution to which the loan application was made. We control for this by including the dummy variable *Lender type*, which maps the SSBF's lender categories. We collapse the originally reported 21 categories into four overall groups: banks, non-bank financial firms, individuals (owner, family or other), and other lender type. Previous studies have shown that applying for a loan at a "main bank" may improve the likelihood of approval (Lehmann and Neuberger, 2001) as well as influence loan terms (Degryse and Cayseele, 2000; Menkhoff et al., 2006). Thus, we include the variable *Primary bank* which equals 1 if if the financial institution to which the loan application was made is the firm's primary provider of financial services, and 0 otherwise.

Loan Characteristics: For firms with at least one loan application, we observe the type of loan that was most recently applied for, which we control for using the dummy variable *Loan type*, that maps the SSBF's six categories.[12] For approved loans, we also control for the maturity of the loan, measured as the logarithm of the maturity in months. The loan amount applied for has been shown to be significantly associated with collateral (Leeth and Scott, 1989; Degryse and Cayseele, 2000; Jiménez et al., 2006; Berger et al., 2011b). To account for this, we include the amount applied for scaled by the firm's total sales. Besides collateral, the other main loan term that we treat as endogenous is the interest rate of the loan.

Environmental Factors: To control for geographic information, two variables are included. The first one controls for whether the headquarters of the firm are located in an urban (as opposed to a rural) area. The dummy variable *Metropolitan area* takes the value 1 if the firm's headquarters are located in a Metropolitan Statistical Area (MSA), and 0 otherwise. The second is a dummy variable for each of the nine U.S. Census Division regions[13], which is the most detailed location information available for the survey firms. To account for regional bank market structure, we include the dummy variable *Banking concentration*, which equals 1 if the Herfindahl-Hirschman Index (HHI) reported in the surveys is greater than or equal to 1800, and zero otherwise. Finally, dummies for survey release are included to control for possible unexplained differences in the three surveys.

12 The loan types include new credit line, capital lease, mortgage, vehicle loan, equipment loan and other loan.

13 New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

We include at least one exclusion restriction in each equation. To identify the credit demand model (equation 1), we make use of survey responses to the question "What is the most important problem facing your business today?", with possible answers distributed over 28 alternatives. One of these refers specifically to funding issues – "Cash flow". We account for this response using the dummy variable *Cash flow problem*. The logic of this variable can be thought of as resting on the theory of pecking order financing. Firms with internal funding problems are assumed to have a high demand for external financing (Myers and Majluf, 1984).

The source of identification in our credit application model (equation 2) comes from a variable *% purchased by trade credit*, which captures the percentage of purchases the firm makes using trade credit. Two mutually non-exclusive arguments back up the use of this variable. The first one is intuitive: if trade credit is a relatively expensive source of financing (compared to bank credit), firms that rely to a large extent on trade credit may be more inclined to apply for a bank loan. The second argument relies on the theoretical results of Biais and Gollier (1997), who argue that high reliance on trade credit from suppliers may signal firm quality in the sense that the firm is trusted by these suppliers; high-quality firms may, in turn, be less subject to discouragement. (The theory also implies that if this signal can be conveyed to a lender/bank, then high reliance on trade credit may also increase the probability of loan approval, by reducing adverse selection.)

The source of unique variation in the approval model (equation 3) comes from a single dummy variable, indicating if ownership of the firm has transferred at some point since it was founded, previously used by Levenson and Willard (2000). The reasoning is that firms for which a transfer of ownership has taken place, and which are still in business, should be more viable. Consequently, ownership transfer signals firm quality, which should positively affect the probability of approval, conditional on applying (but should be uncorrelated with the application as such). Note that also the loan, lender and relationship characteristics included in the approval equation provides additional sources of variation vis-à-vis the previous stages in the selection process.

Identification in the final instrumental variables estimation of loan size rationing is a key concern. The objective is to find a set of instruments that provide sufficient unique variation – after controlling for all firm, owner, relationship and loan/lender characteristics – to predict *both* collateral and loan interest rates, but which at the same time do not directly determine loan size rationing. This is a challenge.[14] We consider the following candidate instruments drawn from previous literature as well as based more on general economic reasoning.

For the loan rates, we consider two primary candidates. The first instrument is a simple dummy variable indicating if the loan interest rate is floating. Results of several previous studies (Berger and Udell, 1990; Brick and Palia, 2007; Chakravarty and Yilmazer, 2009; Cowling, 2010) indicate that the interest cost of floating-rate loans is lower than on fixed-rate loans, but the premium charged by banks for assuming the interest rate risk is unlikely to directly predict rationing (or other loan terms), suggesting that the floating-rate indicator may be a unique source of variation in the loan spread. The second instrument is the average yield on 10-year U.S. Treasury bonds in the month when the loan was approved (sourced from the Federal Reserve's website). We do not match maturities precisely (the average loan maturity in the sample is approximately 5 years).

For collateral, we construct two variables. The first is the dummy variable *Existing collateral*, which equals 1 when collateral and/or guarantees were pledged on outstanding loans. This variable can be considered as a proxy of collateral availability. Since existing loans tie up the pledged assets, they may use up collateral capacity, which may affect the likelihood of collateralization but is unlikely to affect the lender's decision to restrict credit if the loan is *not* collateralized

14 Our estimation approach relies on the assumption that the maturity of the loan is more likely to be driven by exogenous preferences, or – at a minimum – that collateral requirements, loan interest rate and relative loan amount granted are more likely to be set for given maturity than the other way around.

(i.e., the only effect on rationing is the indirect one, via collateral on the most recent loan). Collateral on existing loans may also capture the firm's revealed preference for pledging collateral, which is likely to affect the probability of collateralization, but should not directly affect the lender's rationing decision (for given likelihood to require collateral). For the second variable we make use of the time series of the net percentage of banks tightening collateral requirements from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS).

Both Treasury yields and the SLOOS data are pure time series (at quarterly frequency in the case of the SLOOS) and do not provide any cross-sectional variation as such, but since we observe the date at which a loan was contracted and the surveys cover loans contracted over three different time periods of more than three years' duration each, the time variation in these variables indirectly provides a great deal of variation also over the cross section of approved loans.

4.6 *Descriptive Statistics*

Basic descriptive statistics, in the form of by-subsample means, standard deviations and univariate difference tests of the included variables, are presented in Table 22. The table also shows the extent of sample truncation at each stage in the analysis. Of the total sample (11,503 observations), roughly 46 percent are identified as having a non-zero credit demand. Of these, about 28 percent are "truly discouraged borrowers" (Jappelli, 1990), that never make any loan application. Among the 3,785 firms that do apply, only about 15 percent are turned down completely (i.e., are quantity-rationed), leaving 3,213 firms for the final instrumental-variables estimation, 9.5 percent of which are loan size rationed.

Panel A splits the sample into two groups, those firms that have demand for credit and those who do not need credit. Differences between these two groups are apparent when one considers firm and relationship characteristics. The univariate comparison shows that, on average, credit demand firms are younger, less profitable and riskier than non-demand firms. But when it comes to firm size (measured both by the total sales and the number of employees), credit demand firms are larger than non-credit seekers. They also have, on average, more lending relationships.

Panel B further divides the sample of firms with credit demand into two groups, applicant and non-applicant firms. We observe that applicant firms are considerably larger (measured by the total sales and the number of employees) and older on average than non-applicant firms, suggesting that smaller and younger firms are more likely to be discouraged. Similarly, a lower proportion of applicant firms has a history of bankruptcy or delinquency.

In terms of personal characteristics, owners of applicant firms are older, more experienced, and are more likely to have a college degree compared to non-applicant owners, suggesting that owners with lower levels of human capital may be discouraged from submitting a loan application. We also observe that a higher proportion of non-applicant firms have Asian, African American or Hispanic owners, possibly reflecting that minority business owners have an expectation of discrimination in the credit market. However, this result could also reflect self-rationing (self-screening) due to socio-economic factors, as these groups tend to have lower education and income levels. Similarly, while the lower proportion of female ownership for applying firms may be due to expectations of gender discrimination, female owners tend to have lower levels of human capital (Boden and Nucci, 2000; Fairlie and Robb, 2009) and lower sales turnover, job creation and profitability (Rosa et al., 1996).

In line with expectation, the unconditional mean comparison also shows that applicant firms entertain a larger number of financial service providers compared to non-applicant firms. Applicant firms also report considerably higher percentage of purchases made by trade credit.

Table 22. Univariate Analysis: Credit demand, Applied, Approved and Full amount granted firms

This table presents a univariate analysis of the means of the variables used in this study. Columns [1] and [2] present the means and standard deviations (in the bracket) of the variables for firms with credit demand and those who do not need credit, respectively; column [3] displays the difference in means of the variables presented in the first two columns. Columns [4] and [5] report the means and standard deviations of the variables for credit applicant and non-applicant firms, respectively; the difference in means of the variables between these two groups is reported in column [6]. Columns [7] and [8] present the means and standard deviations of the variables for approved and non-approved firms, respectively; column [9] displays the difference in means of the variables between these two groups of firms. While the means and standard deviations of the variables for full amount granted and loan size rationed firms are presented in columns [10] and [11], the difference in means of the variables between these two groups is displayed in column [12]. The t test of the statistical significance of the differences in means is indicated by asterisk, where ***, **, and * indicate significance at the 1% level, the 5% level and the 10% level, respectively.

	Demand [N = 7,650]			Applied [N = 2,915]			Approved [N = 2,030]			Full amt granted [N = 1,750]		
	Demand=1 [N = 2,915] [1]	Demand=0 [N = 4,735] [2]	[3=1-2]	Applied=1 [N = 2,030] [4]	Applied=0 [N = 885] [5]	[6=4-5]	Approved=1 [n = 1,750] [7]	Approved=0 [N = 280] [8]	[9=7-8]	Full amt Granted=1 [N = 1,624] [10]	Full amt Granted=0 [N = 126] [11]	[12 = 10 -11]
Total sales	4.728	3.466	1.262***	6.205	0.894	5.312***	7.064	1.381	5.683***	7.103	6.693	0.410
	(13.75)	(12.96)	(0.250)	(15.80)	(3.386)	(0.417)	(16.86)	(5.265)	(0.711)	(16.99)	(15.65)	(1.016)
Number of employees	37.20	25.76	11.441***	46.92	11.98	34.931***	52.08	17.92	34.156***	51.74	55.30	−3.555
	(65.87)	(53.38)	(1.112)	(72.58)	(32.39)	(1.972)	(76.08)	(36.86)	(3.247)	(75.47)	(81.76)	(4.586)
Firm age	14.19	16.45	−2.259***	15.39	11.10	4.292***	16.17	11.01	5.153***	16.23	15.54	0.696
	(12.33)	(13.11)	(0.239)	(13.13)	(9.261)	(0.375)	(13.53)	(9.532)	(0.590)	(13.52)	(13.64)	(0.816)
Profitability	0.124	0.179	−0.055***	0.118	0.142	−0.024*	0.117	0.122	−0.005	0.116	0.121	−0.005
	(0.347)	(0.390)	(0.007)	(0.304)	(0.439)	(0.011)	(0.286)	(0.393)	(0.014)	(0.286)	(0.285)	(0.017)
Leverage	3.709	1.622	2.087***	3.822	3.387	0.435	3.756	4.208	−0.452	3.542	5.778	−2.235*
	(14.86)	(10.01)	(0.246)	(14.88)	(14.81)	(0.488)	(14.88)	(14.85)	(0.704)	(14.43)	(18.53)	(0.915)
Firm default history	0.277	0.0982	0.178***	0.244	0.361	−0.118***	0.210	0.432	−0.221***	0.203	0.280	−0.076**
	(0.447)	(0.298)	(0.007)	(0.429)	(0.481)	(0.014)	(0.408)	(0.496)	(0.019)	(0.402)	(0.450)	(0.025)
Low diversification	0.575	0.677	−0.102***	0.541	0.661	−0.120***	0.533	0.591	−0.058**	0.539	0.470	0.069*
	(0.494)	(0.468)	(0.009)	(0.498)	(0.473)	(0.015)	(0.499)	(0.492)	(0.023)	(0.499)	(0.500)	(0.030)
Owner age				49.93	48.04	1.892***	50.37	47.44	2.939***	50.41	50.02	0.392
				(10.66)	(10.43)	(0.327)	(10.61)	(10.64)	(0.482)	(10.56)	(11.02)	(0.641)
Asian ownership				0.0438	0.0652	−0.021**	0.0398	0.0664	−0.027**	0.0388	0.0495	−0.011
				(0.205)	(0.247)	(0.007)	(0.196)	(0.249)	(0.009)	(0.193)	(0.217)	(0.012)
AfrAm ownership				0.0720	0.177	−0.104***	0.0432	0.233	−0.189***	0.0391	0.0825	−0.043***
				(0.259)	(0.381)	(0.009)	(0.203)	(0.423)	(0.011)	(0.194)	(0.276)	(0.012)
Hispanic ownership				0.0510	0.104	−0.053***	0.0445	0.0874	−0.043***	0.0447	0.0429	0.002
				(0.220)	(0.305)	(0.008)	(0.206)	(0.283)	(0.010)	(0.207)	(0.203)	(0.012)
Female ownership				0.156	0.271	−0.114***	0.144	0.227	−0.084***	0.145	0.129	0.016
				(0.363)	(0.444)	(0.012)	(0.351)	(0.419)	(0.016)	(0.352)	(0.335)	(0.021)
Owner experience				19.93	16.28	3.651***	20.50	16.73	3.778***	20.51	20.40	0.119
				(10.81)	(10.28)	(0.329)	(10.84)	(10.08)	(0.487)	(10.75)	(11.72)	(0.655)
College				0.531	0.426	0.105***	0.549	0.430	0.119***	0.546	0.578	−0.032

(Continued on next page)

Table 22. Univariate Analysis: Credit demand, Applied, Approved and Full amount granted firms (Continued)

	Demand [N = 7,650]			Applied [N = 2,915]			Approved [N = 2,030]			Full amt granted [N = 1,750]		
	Demand=1 [N = 2,915] [1]	Demand=0 [N = 4,735] [2]	[3=1-2]	Applied=1 [N = 2,030] [4]	Applied=0 [N = 885] [5]	[6=4-5]	Approved=1 [n = 1,750] [7]	Approved=0 [N = 280] [8]	[9=7-8]	Full amt Granted=1 [N = 1,624] [10]	Full amt Granted=0 [N = 126] [11]	[12 = 10 -11]
				(0.499)	(0.495)	(0.015)	(0.498)	(0.496)	(0.023)	(0.498)	(0.495)	(0.030)
Owner share				71.04	84.23	−13.193∗∗∗	69.52	79.51	−9.993∗∗∗	69.74	67.41	2.328
				(29.25)	(24.21)	(0.862)	(29.52)	(26.15)	(1.318)	(29.53)	(29.41)	(1.782)
Owner default history				0.141	0.364	−0.223∗∗∗	0.0989	0.378	−0.279∗∗∗	0.0969	0.119	−0.022
				(0.348)	(0.481)	(0.012)	(0.299)	(0.485)	(0.015)	(0.296)	(0.324)	(0.018)
Number of sources	4.080	3.109	0.971∗∗∗	4.593	2.746	1.848∗∗∗	4.820	3.320	1.500∗∗∗	4.828	4.747	0.081
	(2.151)	(1.948)	(0.038)	(2.081)	(1.712)	(0.061)	(2.048)	(1.786)	(0.091)	(2.051)	(2.027)	(0.123)
Relationship length							7.614	5.320	2.294∗∗∗	7.711	6.678	1.033
							(9.003)	(6.645)	(0.396)	(8.998)	(9.014)	(0.544)
Distance							84.93	58.47	26.466∗	84.53	88.83	−4.308
							(297.3)	(252.9)	(13.272)	(292.9)	(337.4)	(17.979)
Referral										0.0437	0.0625	−0.019
										(0.204)	(0.242)	(0.013)
Previous loan										0.0553	0.0493	0.006
										(0.229)	(0.217)	(0.014)
Primary bank										0.313	0.280	0.034
										(0.464)	(0.450)	(0.028)
Amount requested							0.917	0.219	0.698∗∗∗	0.895	1.124	−0.229
							(4.130)	(0.992)	(0.174)	(4.125)	(4.177)	(0.249)
Maturity										49.36	52.07	−2.713
										(60.74)	(62.12)	(3.681)
Collateral										0.843	0.836	0.007
										(0.364)	(0.371)	(0.022)
#collateral types										1.513	1.724	−0.211∗∗
										(1.206)	(1.410)	(0.074)
Interest rate										7.915	8.197	−0.282
										(2.590)	(2.648)	(0.156)
Metropolitan area	0.787	0.790	−0.003	0.769	0.833	−0.065∗∗∗	0.755	0.843	−0.087∗∗∗	0.752	0.786	−0.034
	(0.410)	(0.408)	(0.008)	(0.422)	(0.373)	(0.013)	(0.430)	(0.364)	(0.019)	(0.432)	(0.411)	(0.026)
Banking concentration				0.506	0.461	0.045∗∗	0.509	0.491	0.018	0.512	0.485	0.027
				(0.500)	(0.499)	(0.015)	(0.500)	(0.500)	(0.023)	(0.500)	(0.501)	(0.030)
Cash flow problem	0.151	0.153	−0.003									
	(0.358)	(0.360)	(0.007)									
% purch. trade credit				75.97	62.13	12.891∗∗∗						

(Continued on next page)

Table 22. Univariate Analysis: Credit demand, Applied, Approved and Full amount granted firms (Continued)

	Demand [N = 7,650]			Applied [N = 2,915]			Approved [N = 2,030]			Full amt granted [N = 1,750]		
	Demand=1 [N = 2,915] [1]	Demand=0 [N = 4,735] [2]	[3=1-2]	Applied=1 [N = 2,030] [4]	Applied=0 [N = 885] [5]	[6=4-5]	Approved=1 [n = 1,750] [7]	Approved=0 [N = 280] [8]	[9=7-8]	Full amt Granted=1 [N = 1,624] [10]	Full amt Granted=0 [N = 126] [11]	[12 = 10 -11]
				(29.53)	(33.49)	(1.546)						
Owner transfer							0.335	0.210	0.125∗∗∗			
							(0.472)	(0.408)	(0.021)			
Existing collateral										0.790	0.757	0.034
										(0.407)	(0.430)	(0.025)
Float rate										0.478	0.503	−0.025
										(0.500)	(0.501)	(0.030)

Panel C sorts the sample of applicant firms into two categories, approved and denied (quantity-rationed) firms. The reported mean differences in terms of basic firm, owner and relationship characteristics largely mimic those between applicant and non-applicant firms. Borrowers whose loan applications are approved are larger (measured by the total sales and the number of employees) and older compared to those whose applications turned down. Regarding demographics, owners of approved firms are older, more experienced, and are more likely to have a college degree, signaling that lenders may put weight on the human capital of the business owners. We also observe that approved firms have lower incidence of African American and Hispanic ownership than denied firms. Regarding lending relationships, firms whose loan applications are approved have longer and a larger number of relationships, and have a closer geographical proximity to their lenders compared to those whose applications are rejected. A lower proportion of approved firms have their headquarters located in metropolitan areas. Firms for which at least one ownership transfer has taken place are on average more likely to be approved for loans, in line with expectation.

Panel D, finally, classifies the sub-sample of approved firms into loan-size-rationed and full-amount-granted groups. Unconditional mean comparisons show that differences across these two groups are markedly smaller than at previous stages. Rationed firms are about 20 percent younger. They also on average have significantly *lower* leverage (at less than 1/3 of that of non-rationed firms), but due to very high variance of the debt/equity ratio, this difference is significant only at the 10 percent level. The same goes for the 25 percent longer duration of the relationship with the lender of size-rationed firms. We see no systematic differences in either collateral use in general (about 60 percent of both rationed and non-rationed loans are collateralized), or in the number of collateral types pledged.

5 REGRESSION RESULTS

5.1 *Benchmark Results*

To determine whether collateral plays an independent role in helping reduce rationing in small business lending, we start by running simple, single-equation regressions of the main final-stage equation of loan size rationing to provide a "benchmark" with which to compare our final estimation. In this baseline model, a type of model that has traditionally been estimated, no corrections have been made, either for sample selection bias or for endogenously determined loan terms. The results are reported in Table 23. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights.

The results of ordinary least square (OLS) regressions using as dependent variable the dummy *Loan size rationing* are presented in columns 1 and 2 of Table 23. The two columns differ only in that collateral in the first column is measured by the simple dummy variable *Collateral*, and in second column as *#collateral types*. The probit models estimating the effects of collateral on the probability of being loan-size rationed are reported in columns 3 and 4, and also differ only in the way that collateral is measured. To examine the collateral effect on the magnitude of loan-size rationing, we estimate tobit regressions using as dependent variable the truncated variable *Proportion rationed* in columns 5 and 6.

As evident from the table, the estimations offer little evidence of the role of collateral in reducing loan size credit rationing. The coefficients on collateral are statistically insignificant in four, and significant at the 10 percent level in two regressions. Even the significant coefficients imply a relatively small effect of collateral on rationing. For example, the coefficient estimate of -0.228 in the probit model in column 3 corresponds to a marginal reduction of the probability of experiencing loan size credit rationing of approximately 9 percentage points when the loan contract includes collateral.[15] This weak result leaves open the question of whether collateral has an independent role in reducing credit rationing when other factors are controlled for.

The failure to establish a convincing empirical link supports our argument that results from a single-equation rationing model may be susceptible to potential biases. First, even size-rationed loans are approved loans. If collateral reduces also quantity rationing (and possibly also self-rationing), studying approved loans only will underestimate the effect of collateral for rationing in general (the selection bias). Second, if "riskier" firms are both more likely to use collateral and more likely to be rationed, as in the argument of Berger and Udell (1992) for instance, then there may be two opposing effects of collateral on rationing in single-equation models: a negative effect in line with standard theoretical predictions, and a positive effect stemming from the co-determination of collateral and rationing by (observed or unobserved) firm characteristics (the endogeneity bias).

As to the importance of control variables, the results show that only a few variables have a significant impact. In particular, coefficients for the variable capturing a firm's credit history are positive and highly significant in all regressions, suggesting that the probability of loan size rationing and the proportion of rationed amount increase for small businesses with bankruptcy or business delinquency track records, which is in accordance with expectation. Unlike what is generally perceived in the literature on gender discrimination, female business ownership tends to reduce the probability of rationing. The marginally positive coefficient on *Distance* (in columns 1 through 4) is consistent with the geographic credit rationing theory. Moreover, the estimated coefficient on *Metropolitan area* is positive (and significant at the 10 percent level), indicating that small businesses whose headquarters are located in the metropolitan areas are more likely to experience rationing.

15 Using the rule of thumb that probit coefficient estimates divided by 2.5 are a close approximation of the marginal effect on probability (Wooldridge, 2002).

Table 23. Benchmark Results: Collateral Effects on Loan-Size Rationing

This table presents the benchmark results of collateral effects on loan size rationing using a single-equation model. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise; *Proportion rationed* is defined as one minus the proportion of the loan amount granted. The independent variable of interest *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; # *collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Columns (1) and (2) report the results of ordinary least square (OLS) regression using as dependent the dummy variable *Loan size rationing*, and they differ only in the way that collateral is measured. Columns (3) and (4) display the results from the probit models estimating the effects of collateral on the probability of being loan size rationed, and also differ only in the way that collateral is measured. The results of tobit regressions using as dependent the truncated variable *Proportion rationed* are presented in columns (5) and (6). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Loan size rationing								*Proportion rationed*			
	OLS				Probit				Tobit			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Collateral variables												
Collateral	−0.034	(0.021)			−0.228*	(0.125)			−0.133*	(0.074)		
#collateral types			−0.000	(0.007)			−0.001	(0.040)			−0.005	(0.023)
Firm characteristics												
Log(Total sales)	−0.003	(0.009)	−0.004	(0.009)	−0.022	(0.053)	−0.025	(0.053)	−0.025	(0.034)	−0.027	(0.034)
Log(Number of employees)	−0.001	(0.010)	−0.000	(0.010)	−0.011	(0.060)	−0.008	(0.060)	0.009	(0.036)	0.012	(0.036)
Log(Firm age)	0.001	(0.010)	0.001	(0.010)	0.018	(0.066)	0.019	(0.065)	0.004	(0.037)	0.004	(0.037)
Profitability	0.005	(0.025)	0.008	(0.025)	0.048	(0.163)	0.066	(0.163)	0.053	(0.094)	0.063	(0.095)
Leverage	0.001	(0.001)	0.001	(0.001)	0.003	(0.003)	0.003	(0.003)	0.001	(0.001)	0.001	(0.001)
Firm default history	0.042**	(0.020)	0.042**	(0.020)	0.294***	(0.113)	0.292***	(0.113)	0.169**	(0.067)	0.168**	(0.067)
Low diversification	−0.002	(0.015)	−0.001	(0.015)	0.006	(0.094)	0.011	(0.093)	0.006	(0.059)	0.010	(0.058)
Owner characteristics												
Log(Owner age)	0.033	(0.046)	0.037	(0.046)	0.274	(0.275)	0.293	(0.276)	0.236	(0.166)	0.246	(0.167)
Asian ownership	0.055	(0.046)	0.057	(0.046)	0.265	(0.198)	0.264	(0.197)	0.144	(0.112)	0.142	(0.112)

(Continued on next page)

Table 23. Benchmark Results: Collateral Effects on Loan-Size Rationing (Continued)

	Loan size rationing								*Proportion rationed*			
	OLS				Probit				Tobit			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
AfrAm ownership	0.006	(0.033)	0.009	(0.032)	0.032	(0.195)	0.039	(0.193)	0.020	(0.115)	0.023	(0.114)
Hispanic ownership	−0.028	(0.031)	−0.027	(0.031)	−0.157	(0.214)	−0.154	(0.214)	−0.099	(0.120)	−0.097	(0.120)
Female ownership	−0.031*	(0.017)	−0.028*	(0.017)	−0.245**	(0.122)	−0.228*	(0.120)	−0.168**	(0.072)	−0.158**	(0.072)
Log(1 + Owner experience)	−0.016	(0.017)	−0.017	(0.017)	−0.134	(0.100)	−0.137	(0.099)	−0.099	(0.061)	−0.100*	(0.061)
College	0.005	(0.016)	0.005	(0.017)	0.027	(0.102)	0.030	(0.101)	−0.006	(0.060)	−0.003	(0.060)
Owner share	−0.000	(0.000)	−0.000	(0.000)	−0.002	(0.002)	−0.002	(0.002)	−0.001	(0.001)	−0.001	(0.001)
Owner default history	−0.012	(0.024)	−0.014	(0.024)	−0.108	(0.149)	−0.106	(0.151)	−0.049	(0.092)	−0.047	(0.093)
Relationship characteristics												
Number of sources	0.001	(0.005)	0.001	(0.005)	0.013	(0.029)	0.009	(0.029)	0.013	(0.017)	0.011	(0.017)
Log(1 + Relationship length)	−0.008	(0.008)	−0.007	(0.008)	−0.058	(0.054)	−0.053	(0.054)	−0.034	(0.032)	−0.031	(0.032)
Log(1 + Distance)	0.009*	(0.005)	0.009*	(0.005)	0.047*	(0.028)	0.049*	(0.029)	0.025	(0.017)	0.026	(0.017)
Referral	0.012	(0.035)	0.014	(0.035)	0.103	(0.197)	0.107	(0.196)	0.073	(0.119)	0.075	(0.119)
Previous loan	−0.023	(0.027)	−0.024	(0.027)	−0.156	(0.189)	−0.167	(0.187)	−0.077	(0.112)	−0.083	(0.111)
Lender characteristics												
Primary bank	−0.025	(0.016)	−0.024	(0.016)	−0.177	(0.109)	−0.178*	(0.108)	−0.104	(0.066)	−0.105	(0.066)
Loan characteristics												
Interest rate	−0.001	(0.003)	−0.001	(0.003)	−0.005	(0.019)	−0.002	(0.019)	−0.003	(0.012)	−0.002	(0.012)
Log(Maturity)	0.011	(0.008)	0.009	(0.008)	0.071	(0.050)	0.059	(0.049)	0.028	(0.030)	0.021	(0.029)
Amount / Total sales	0.001	(0.001)	0.001	(0.001)	0.005	(0.006)	0.004	(0.006)	0.002	(0.004)	0.002	(0.004)
Environmental factors												
Bank concentration	−0.013	(0.016)	−0.013	(0.016)	−0.058	(0.095)	−0.055	(0.095)	−0.045	(0.056)	−0.043	(0.057)
Metropolitan area	0.024	(0.015)	0.025	(0.015)	0.194*	(0.110)	0.194*	(0.110)	0.114*	(0.065)	0.114*	(0.065)
Loan type	YES		YES		YES		YES		YES		YES	

(Continued on next page)

Table 23. Benchmark Results: Collateral Effects on Loan-Size Rationing (Continued)

	Loan size rationing								*Proportion rationed*			
	OLS				Probit				Tobit			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Lender type	YES		YES		YES		YES		YES		YES	
Organizational type	YES		YES		YES		YES		YES		YES	
Industry	YES		YES		YES		YES		YES		YES	
Region	YES		YES		YES		YES		YES		YES	
Survey	YES		YES		YES		YES		YES		YES	
R-squared	0.045		0.043									
N	2,905		2,905		2,903		2,903		2,905		2,905	

In conclusion, we are unwilling to make too much of these results, given our argument that the estimations are likely to be flawed, due to both sample selection bias and endogeneity. These results are also comparable to those of previous studies only to a limit. The closest results are those of Kirschenmann (2016), who also estimates single-equation models of loan size rationing on firm, relationship and loan characteristics (including collateral), but where the difference is that Kirschenmann (2016) uses panel data, whereas our data is a pooled cross section with non-repeated observations for individual cross-section units, which precludes the possibility to control for unobserved firm heterogeneity. This is a potentially crucial difference, suggesting comparability is limited. Again, then, these results are intended only for comparison with our later results, where we perform estimations controlling for the influence of selectivity and endogeniety issues.

5.2 *trivariate probit selection model*

As discussed earlier, our approach to dealing with the selectivity problem in the loan size rationing estimations is the three-step selection process, which is based on the assumption that credit demand, the propensity to apply for a loan, and the likelihood of being approved are a sequence of interrelated outcomes, necessitating joint estimation and allowing for error correlation. Table 24 reports the estimates of the trivariate probit regression.

The primary focus of this analysis is on the estimates of the correlation coefficients, which are reported at the bottom of Table 24. The estimated correlation coefficients are large and highly significant, supporting our basic premise that credit need, the firm's decision about whether to apply, and the lender's decision whether to approve are closely interrelated. Because the correlation terms take on positive values, the underlying latent variables that may explain these decisions tend to move together. For example, the latent variable that makes firms need credit may also induce them to make a loan application. One factor that influences a firm's application decision is the

Table 24. A Trivariate Probit Selection Model: Demand, Application and Approval

This table presents results from a trivariate probit selection model. Column (1) displays results from a probit regression predicting credit demand (i.e., firms decide whether they need credit or not). Column (2) reports results from a probit regression predicting loan application (i.e., conditional on credit demand, firms decide whether to apply). Column (3) displays results from a probit regression predicting loan approval (i.e., given a firm's credit demand and application decision, lenders decide whether to approve). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Credit demand		Applied		Approved	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Log(Total sales)	−.025	(.015)	.058**	(.023)	.169***	(.041)
Log(Number of employees)	.029	(.022)	.031	(.029)	−.073	(.048)
Log(Firm age)	−.193***	(.020)	−.070**	(.032)	.149**	(.070)
Profitability	−.117***	(.044)	−.174***	(.057)	−.040	(.103)
Leverage	.003**	(.001)	.001	(.002)	.002	(.002)
Firm default history	.702***	(.046)	.280***	(.060)	−.335***	(.125)
Low diversification	−.069*	(.037)	−.064	(.046)	−.169**	(.077)
Log(Owner age)			−.220**	(.010)	.101	(.200)
Asian ownership			.021	(.078)	−.169	(.150)
AfrAm ownership			.044	(.068)	−.612***	(.141)
Hispanic ownership			−.109	(.078)	−.274**	(.133)
Female ownership			−.002	(.044)	−.085	(.090)
Log(1 + Owner Experience)			−.033	(.039)	−.184**	(.079)
College			.028	(.036)	.213***	(.080)
Primary owner share			−.001	(.001)	.000	(.002)
Owner default history			−.190***	(.050)	−.596***	(.099)
Number of sources	.197***	(.012)	.234	(.015)	.200***	(.032)
Log(1 + Relationship length)					.046	(.044)
Log(1 + Distance)					.017	(.023)
Amount / Total sales					.006	(.004)
Metropolitan area	−.078*	(.042)	−.208***	(.055)	−.371***	(.100)
Banking concentration			.003	(.036)	−.132*	(.079)
Cash flow problem	.125***	(.040)				
% purchase trade credit			.001**	(.001)		
Owner transfer					.059	(.085)
Loan type	NO		NO		YES	
Lender type	NO		NO		YES	
Organizational type	YES		YES		YES	
Industry	YES		YES		YES	
Region	YES		YES		YES	
Survey	YES		YES		YES	
Error correl., demand-appl.			.97***			
Error correl., demand-appr.					.54**	
Error correl., appl.-appr.					.51**	

expectation that the firm maintains concerning the likelihood of approval/rejection. The positive value for the correlation term between application and approval suggests that the latent variable that influences this expectation also influences the lender's decision whether to approve the loan. In sum, the large positive values and significance of the correlation terms lend credence to the appropriateness of the framework of joint estimation using a trivariate probit model that explicitly accounts for the interrelated nature of the credit demand, application and approval decisions.

5.2.1 *Credit demand*

Column 1 of Table 24 displays results from a probit regression estimating factors influencing small businesses demand for credit financing. The results show a high degree of correspondence with the univariate results depicted in Table 22, with the exception that firm size (measured as the total sales and the number of employees) appears to have no significant effect on credit demand. We observe that credit demand depends inversely on firm age. One explanation may be that older firms have access to alternative sources of financing; also, investment opportunities are typically thought to decline in firm age; hence older firms may seek less external financing.

The significantly positive coefficient on the variable identifying firms that list cash flow as a major problem indicates that firms that generate low (insufficient) cash flows desire more credit financing. This result accords well with the pecking order financing hypothesis. One could also apply a similar reasoning for the highly significant and negative coefficient on profitability, which suggests that profitable firms are less likely to demand credit, perhaps because they want to exhaust their internal funds. This result is consistent with the finding of Kayhan and Titman (2007) that more profitable firms tend to employ less credit financing. The result that less profitable firms are more likely to seek credit may suggest that adverse selection may be a potential problem. This view is supported by the positive and significant coefficient on leverage and the variable capturing a firm's bankruptcy or delinquency track records.

5.2.2 *Loan application*

Column 2 of Table 24 reports results from a probit regression estimating factors that influence a firm's decision whether to apply, given the firm's credit demand. The percentage purchased by trade credit has a positive and significant effect on the probability of loan application, so does firm size (measured by the total sales). We also observe that the probability of loan application is negatively associated with firm age. Profitability likewise decreases the likelihood of applying, whereas we find a highly significant and positive coefficient on the variable capturing a firm's default track record, consistent with an adverse selection explanation – that is, the self-selection of small businesses with a history of bankruptcy or delinquency, which may adversely affect the average quality of the application pool.

The conditional loan application effects of owner characteristics are substantially weaker than the univariate result tends to suggest. The only significant variables we find are owner age and the variable capturing the owner's past bankruptcy or delinquency, both negatively affecting the probability of a loan application. We interpret this finding along the line that older groups of small business owners and those with default records are more likely to be discouraged. This explanation is consistent with the finding of Han et al. (2009) that the probability of being discouraged is positively associated with owner age. After controlling for other key factors, we find no evidence that supports self-rationing on the basis of ethnic minorities.

Apart from the characteristics of the firm and its owner, the application decision also depends on relationships: the significantly positive coefficient on the number of sources of financial services suggests that firms with multiple relationships are less likely to be discouraged. This result is reasonable as firms can make repeated (and/or multiple) applications to different creditors. We also observe that firms whose headquarters are located in the metropolitan area are less likely to make a loan application.

5.2.3 *Loan approval*

Column 3 of Table 24 displays results from a probit regression predicting the lender's decision whether to approve the application or not, given the firm's credit demand and loan application decision. The coefficients on firm size and firm age are positive and significant. One could provide two plausible explanations for this result: first, firm size may be a reflection of success and availability of collateralizable assets; second, age could be a reflection of survival and information transparency (or reputational capital), making lenders more willing to approve loans. The significantly negative coefficient on the variable capturing a firm's credit history suggests that lenders place weight on previous default records, and are more likely to turn down loan applications of firms with the history of bankruptcy or delinquency.

The result also reveals that demographic characteristics of the owners influence the likelihood of being approved. Even after controlling for other key factors, we find evidence that minority ownership significantly reduces loan approval probability, as the coefficients on African American and Hispanic owners are significantly negative. In contrast, lenders do not appear to treat loan applicants differently on the basis of gender. Consistent with expectation, holding a college degree has a positive impact on the chances of loan approval. The negative coefficient on owner experience is, however, counterintuitive.

Aside from encouraging firms to submit their loan application, the number of sources of financial services also influences a lender's decision whether to approve the loan application. We also find some evidence that loan applications from concentrated banking markets tend to have lower likelihood of approval, suggesting that competitive banking markets increase access to credit for small businesses. Applications made from metropolitan areas also have lower approval rates.

5.3 *Instrumental-Variables Estimation*

Thus far we have shown that credit demand, application and approval are an interrelated sequential process, suggesting that the uncorrected results in Table 23 may be suffering from biases arising from non-random selection. To mitigate this concern, inverse Mill's ratios from the credit demand, loan application and approval equations are included in the final loan size rationing equation. In addition to the selectivity issues, collateral use may also be endogenously determined with other loan terms, potentially biasing coefficient estimates and confounding inference. To account for this effect, we estimate the loan size rationing equation using an instrumental variables approach.

5.3.1 *Validity and Relevance of Instruments*

The IV estimation method relies on the assumption that the excluded instruments are uncorrelated with the errors from the credit rationing equation, and that they are sufficiently correlated with the included endogenous variables (collateral and interest rates in our case). To ensure the validity and relevance of our instruments, we diagnose on the regression specification, and a representative set of the test statistics generated from the IV-GMM regression are presented in Table 25.

We further test the strength of the instruments using "weak identification" tests. Since our results are heteroskedastic robust, the valid test statistic is the Kleibergen and Paap's (2006) rank Wald F-statistic. The row marked "10% maximal IV relative bias" contains Stock and Yogo's (2005) critical values for the tests that the instruments are not sufficiently correlated with the endogenous regressors based on the bias of the IV estimator relative to the bias of the OLS estimator. If we are willing to tolerate a 10% relative bias, we can conclude that our instruments are are not weak as the test statistics are equal to or above the critical value of 7.56. We also address the significance of the endogenous regressors in the structural equation being estimated, which we carry out using "weak instrument robust inference" tests.

Table 25. Testing the Validity and Relevance of Instruments

This table presents test statistics and the corresponding p-values generated from IV-GMM regressions of the credit rationing equation 4. The test statistics reported in column (1) are generated when the included endogenous variables are *Collateral* and interest rates), and those displayed in column (2) are generated when the included endogenous variable are # *collateral types* and interest rates. *10% maximal IV relative bias* presents Stock and Yogo's (2005) critical values for the weak identification test based on the bias of the IV estimator relative to the bias of the OLS estimator.

	Collateral		*#collateral types*	
	(1)		(2)	
	Test statistic	P-value	Test statistic	P-value
Overidentification test				
Hansen J statistic	$\chi^2(2) = 0.819$	$P = 0.66$	$\chi^2(2) = 0.09$	$P = 0.96$
Underidentification test				
Kleibergen-Paap rk LM	$\chi^2(3) = 26.96$	$P = 0.00$	$\chi^2(3) = 25.57$	$P = 0.00$
Weak identification test				
Kleibergen-Paap Wald rk F	8.11		7.56	
10% maximal IV relative bias	7.56		7.56	
Weak-instrument-robust inference				
Anderson-Rubin Wald	$\chi^2(4) = 8.24$	$P = 0.08$	$\chi^2(4) = 8.24$	$P = 0.08$
Stock-Wright LM	$\chi^2(4) = 12.49$	$P = 0.01$	$\chi^2(4) = 12.49$	$P = 0.01$
Endogeneity test	$\chi^2(2) = 5.02$	$P = 0.08$	$\chi^2(2) = 7.77$	$P = 0.02$

The test statistics for both Anderson and Rubin (1949) and Stock and Wright (2000) tests are significant. These tests reject the null hypothesis that the coefficients of the endogenous regressors are jointly equal to zero. Finally, the row marked "Endogeneity test" contains results for a test of the null hypothesis that the instrumented regressors can be treated as an endogenous variable, with interpretation in line with a standard Hausman test. The significant test statistics suggest that collateral and loan interest rate are jointly endogenous in the credit rationing equation, and that instrumental variable regression is the relevant approach.

5.3.2 *IV-GMM and CUE Regression Results*

Table 26. IV-GMM and CUE Regression Results

This table presents results from regressions that examine the impact of collateral on loan size rationing using instrumental variable estimation and controlling for selectivity issues. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise. The independent variable of interest *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; # *collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Columns (1) and (2) report the IV-GMM estimates, and they differ only in the way that collateral is measured. Columns (3) and (4) display results from regressions estimated using the continuously updated estimator (CUE) of Hansen et al. (1996). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	IV-GMM (Dep. var: rationing dummy)				CUE (Dep. var: rationing dummy)			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Collateral variables								
Collateral	−0.151 ∗∗	(0.076)			−0.152 ∗∗	(0.077)		
#collateral types			−0.073 ∗∗	(0.036)			−0.073 ∗∗	(0.036)
Firm characteristics								
Log(Total sales)	−0.024 ∗∗	(0.012)	−0.024∗	(0.013)	−0.024∗	(0.012)	−0.024∗	(0.013)
Log(Number of employees)	0.014	(0.010)	0.016	(0.010)	0.014	(0.010)	0.016	(0.010)
Log(Firm age)	0.000	(0.020)	0.002	(0.020)	0.000	(0.020)	0.002	(0.020)
Profitability	−0.008	(0.037)	0.001	(0.040)	−0.009	(0.038)	0.001	(0.040)
Leverage	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Firm default history	0.033	(0.056)	0.040	(0.058)	0.033	(0.057)	0.040	(0.058)
Low diversification	0.011	(0.018)	0.007	(0.020)	0.011	(0.018)	0.007	(0.019)
Owner characteristics								
Log(Owner age)	−0.010	(0.060)	−0.023	(0.061)	−0.011	(0.060)	−0.023	(0.061)
Asian ownership	0.047	(0.053)	0.043	(0.053)	0.046	(0.052)	0.043	(0.053)
AfrAm ownership	0.068	(0.043)	0.073	(0.045)	0.068	(0.043)	0.073	(0.045)

(Continued on next page)

Table 26. IV-GMM and CUE Regression Results (Continued)

	IV-GMM (Dep. var: rationing dummy)				CUE (Dep. var: rationing dummy)			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Hispanic ownership	0.009	(0.041)	0.007	(0.043)	0.009	(0.041)	0.007	(0.043)
Female ownership	−0.024	(0.021)	−0.016	(0.021)	−0.024	(0.021)	−0.016	(0.021)
Log(1 + Owner experience)	0.000	(0.021)	−0.001	(0.022)	0.000	(0.021)	−0.001	(0.022)
College	−0.012	(0.020)	−0.012	(0.020)	−0.012	(0.020)	−0.012	(0.020)
Primary owner share	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)
Owner default history	0.037	(0.039)	0.040	(0.041)	0.037	(0.039)	0.040	(0.041)
Relationship characteristics								
Number of sources	−0.024	(0.023)	−0.019	(0.024)	−0.024	(0.023)	−0.019	(0.024)
Log(1 + Relationship length)	−0.023 ∗∗	(0.010)	−0.023 ∗∗	(0.010)	−0.023 ∗∗	(0.010)	−0.023 ∗∗	(0.010)
Log(1 + Distance)	0.009	(0.006)	0.009	(0.006)	0.009	(0.006)	0.009	(0.006)
Referral	−0.013	(0.041)	−0.011	(0.043)	−0.013	(0.041)	−0.011	(0.043)
Previous loan	−0.007	(0.029)	−0.006	(0.031)	−0.007	(0.030)	−0.006	(0.031)
Lender characteristics								
Primary bank	−0.006	(0.018)	−0.003	(0.020)	−0.006	(0.019)	−0.003	(0.019)
Loan characteristics								
Interest rate	−0.020	(0.015)	−0.026∗	(0.016)	−0.020	(0.015)	−0.026∗	(0.016)
Log(Maturity)	0.006	(0.011)	0.004	(0.011)	0.006	(0.011)	0.004	(0.011)
Amount / Total sales	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Environmental factors								
Bank concentration	0.010	(0.019)	0.017	(0.020)	0.010	(0.019)	0.017	(0.020)
Metropolitan area	0.058 ∗∗	(0.026)	0.061 ∗∗	(0.028)	0.058 ∗∗	(0.026)	0.061 ∗∗	(0.028)
Inverse Mills ratios								
Demand Mill's ratio	−0.069	(0.177)	−0.078	(0.179)	−0.069	(0.178)	−0.079	(0.179)
Applied Mill's ratio	−0.030	(0.181)	0.007	(0.183)	−0.030	(0.182)	0.007	(0.183)
Approval Mill's ratio	−0.176 ∗∗	(0.076)	−0.193 ∗∗	(0.079)	−0.176 ∗∗	(0.076)	−0.193 ∗∗	(0.079)
Loan type	YES		YES		YES		YES	

(Continued on next page)

Table 26. IV-GMM and CUE Regression Results (Continued)

	IV-GMM (Dep. var: rationing dummy)				CUE (Dep. var: rationing dummy)			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Lender type	YES		YES		YES		YES	
Organizational type	YES		YES		YES		YES	
Industry	YES		YES		YES		YES	
Region	YES		YES		YES		YES	
Survey	YES		YES		YES		YES	
N	2,340		2,340		2,340		2,340	

Table 26 reports results from regressions that examine the impact of collateral on loan size rationing using instrumental variable estimation. The first two columns report the IV-GMM estimates on which the above identification tests are based, with corresponding first stage regressions for the instrumented variables in Appendix A. Column 1 shows that the estimated coefficient on the dummy variable *Collateral* is negative and statistically significant at the 5 percent level. Because it is a linear model, the magnitude of the coefficient suggests that pledging collateral reduces the probability of experiencing loan size rationing by about 15 percentage points. When collateral is measured by the number of the number of collateral types (column 2), we essentially get the same results; the coefficient on the variable *#collateral types* is negative and significant at 5 percent. The size of the coefficient suggests that pledging one additional type of collateral reduces the probability of experiencing loan size rationing by about 7 percentage points on the margin. This finding provides direct evidence that supports the information-asymmetry-based explanation of credit rationing and the mitigating role of collateral.

One potential concern with the results in columns 1-2 is that the instruments are not sufficiently strongly associated with the endogenous variables (cf. the weak identification tests), in which case the regular IV-GMM estimator may exhibit finite-sample bias (Stock et al., 2002). Columns 3-4 of Table 26 therefore report the results of the loan size rationing equation re-estimated using using the Continuously Updated Estimator (CUE) of (Hansen et al., 1996), as this estimation method shows better finite-sample properties than alternative IV/GMM procedures, especially in the presence of possible weak instruments (Baum et al., 2007). As can be noted from columns 3 and 4, the results remain essentially unchanged.

Only a few control variables turn out to have a statistically significant impact, although most variables have the expected sign. We note that the control variables that were significant in Table 23 (benchmark results) do not show a statistically significant impact, with the exception of metropolitan area, after controlling for selectivity and endogeneity effects. We find that firm size (measured by total sales) significantly reduces the probability of rationing, as does the duration of the firm-lender relationship. The finding that collateral, firm size, and the length of the firm-bank relationship are among the most important determinants of credit rationing suggests a strong case for explaining credit rationing in terms of lender-borrower information asymmetries.

Turning to the inverse Mill's ratios, columns 1 through 4 show that the estimated coefficient on the inverse Mill's ratio from the approval equation is statistically significant at the 5 percent level, suggesting that the sample selection effect is non-trivial. The negative coefficient suggests that small businesses that have a high likelihood of approval are the ones that are less likely to experience loan size rationing. We also note that the inverse Mill's ratios from credit demand and application equations are statistically insignificant. One explanation for this could be that the selection effects from credit demand and loan application may already be contained in the selection effect from loan approval (note that the approval equation was estimated in Table 24 conditional on demand and application). Based on the significance of the inverse Mill's ratio, we can conclude that the uncorrected benchmark results in Table 23 could be, at least partially, due to selectivity bias.

5.3.3 *IV-Probit and IV-Tobit Regression Results*

As our measure of the dependent variable in columns 1 through 4 of Table 26 is a binary variable, we further examine the impact of collateral on rationing by estimating IV-probit regressions, to compare how the linear-probability-model results stack up against non-linear specifications of the rationing equation. We also estimate the determinants of the relative loan amount rationed (a truncated variable equal to zero for the majority of the sample) using IV-tobit and controlling for selection bias.

Table 27. IV-Probit and IV-Tobit Regression Results

This table presents coefficient estimates from regressions that examine collateral effects on loan size rationing using instrumental variable estimation and controlling for selectivity issues. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise; *Proportion rationed* is defined as one minus the proportion of the loan amount granted (i.e., the supplied loan amount divided by the demanded loan amount). *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and zero for unsecured loans; # *collateral types* is the number of collateral types (including guarantees) that were used to secure a loan. Columns (1) and (2) report the results of IV-probit regressions using as a dependent variable *Loan size rationing*. Columns (3) and (4) display results from IV-tobit regressions using as a dependent variable *Proportion rationed*. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Loan size rationing				*Proportion rationed*			
	IV-Probit				IV-Tobit			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Collateral variables								
Collateral	−0.982**	(0.429)			−0.540**	(0.267)		
#collateral types			−0.449***	(0.147)			−0.278**	(0.128)
Firm characteristics								
Log(Total sales)	−0.160**	(0.079)	−0.135*	(0.074)	−0.092*	(0.048)	−0.088*	(0.051)
Log(Number of employees	0.105	(0.065)	0.103*	(0.059)	0.073*	(0.039)	0.080**	(0.041)
Log(Firm age)	0.020	(0.119)	0.011	(0.108)	0.023	(0.072)	0.021	(0.075)
Profitability	0.015	(0.237)	0.010	(0.218)	0.013	(0.146)	0.011	(0.154)
Leverage	0.002	(0.003)	0.002	(0.003)	0.001	(0.002)	0.001	(0.002)
Firm default history	0.223	(0.321)	0.258	(0.294)	0.121	(0.199)	0.157	(0.208)
Low diversification	0.115	(0.115)	0.054	(0.109)	0.088	(0.072)	0.060	(0.077)
Owner characteristics								
Log(Owner age	0.009	(0.358)	−0.121	(0.318)	0.023	(0.216)	−0.057	(0.219)

(Continued on next page)

Table 27. IV-Probit and IV-Tobit Regression Results (Continued)

	Loan size rationing				*Proportion rationed*			
	IV-Probit				IV-Tobit			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Asian ownership	0.200	(0.243)	0.136	(0.217)	0.119	(0.141)	0.093	(0.144)
AfrAm ownership	0.381	(0.302)	0.398	(0.268)	0.286	(0.194)	0.327*	(0.198)
Hispanic ownership	0.098	(0.300)	0.043	(0.277)	0.053	(0.173)	0.025	(0.182)
Female ownership	−0.174	(0.136)	−0.118	(0.121)	−0.123	(0.081)	−0.102	(0.083)
Log(1 + Owner experience)	−0.047	(0.117)	−0.027	(0.108)	−0.060	(0.072)	−0.051	(0.075)
College	−0.104	(0.121)	−0.086	(0.110)	−0.096	(0.078)	−0.092	(0.081)
Primary owner share	−0.001	(0.002)	−0.000	(0.002)	−0.001	(0.001)	−0.001	(0.001)
Owner default history	0.169	(0.235)	0.200	(0.217)	0.066	(0.145)	0.097	(0.153)
Relationship characteristics								
Number of sources	−0.152	(0.136)	−0.091	(0.130)	−0.075	(0.077)	−0.051	(0.083)
Log(1 + Relationship length)	−0.169***	(0.057)	−0.150***	(0.052)	−0.112***	(0.035)	−0.113***	(0.037)
Log(1 + Distance)	0.048	(0.033)	0.050*	(0.030)	0.025	(0.021)	0.031	(0.022)
Referral	−0.041	(0.246)	−0.014	(0.230)	−0.042	(0.140)	−0.027	(0.149)
Previous loan	−0.031	(0.193)	−0.023	(0.182)	−0.023	(0.116)	−0.021	(0.124)
Lender characteristics								
Primary bank	−0.014	(0.119)	−0.018	(0.110)	−0.002	(0.073)	−0.005	(0.077)
Loan characteristics								
Interest rate	−0.084	(0.105)	−0.144	(0.090)	−0.061	(0.065)	−0.107	(0.069)
Log(Maturity)	0.042	(0.066)	0.028	(0.056)	−0.000	(0.038)	−0.006	(0.038)
Amount / Total sales	0.001	(0.007)	−0.000	(0.007)	−0.000	(0.005)	−0.001	(0.005)
Environmental factors								
Bank concentration	0.086	(0.115)	0.125	(0.105)	0.034	(0.068)	0.065	(0.073)
Metropolitan area	0.429**	(0.172)	0.363**	(0.165)	0.225**	(0.102)	0.217**	(0.108)
Inverse Mills ratios								

(Continued on next page)

Table 27. IV-Probit and IV-Tobit Regression Results (Continued)

	Loan size rationing				*Proportion rationed*			
	IV-Probit				IV-Tobit			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Demand Mill's ratio	−0.542	(1.025)	−0.472	(0.929)	−0.439	(0.638)	−0.466	(0.656)
Applied Mill's ratio	−0.091	(1.107)	0.187	(1.009)	0.089	(0.689)	0.266	(0.712)
Approval Mill's ratio	−1.253∗∗	(0.555)	−1.214∗∗	(0.516)	−0.732∗∗	(0.365)	−0.807∗∗	(0.373)
Loan type	YES		YES		YES		YES	
Lender type	YES		YES		YES		YES	
Organizational type	YES		YES		YES		YES	
Industry	YES		YES		YES		YES	
Region	YES		YES		YES		YES	
Survey	YES		YES		YES		YES	
Wald test	$\chi^2(2) = 4.03$	$P = 0.13$	$\chi^2(2) = 11.51$	0.00	$\chi^2(2) = 4.14$	$P = 0.13$	$\chi^2(2) = 11.19$	$P = 0.00$
N	2,338		2,338		2,340		2,340	

Column 1 of Table 27 displays results from IV-probit regression, where collateral is measured as a dummy variable; column 2 presents results where collateral is measured by the number of pledged assets. Consistent with the results reported in Table 26, we find a negative and significant impact of collateral. Also consistent with the Table 26 results is the finding that the other main determinants of rationing include firm size and the length of the firm-bank relationship, as well as a highly significant selection effect. As for the economic significance of the effect of collateral, the IV-probit estimates suggest a substantially larger impact than the IV-GMM estimates. For example, the coefficient estimate on the collateral dummy in column 1 is -0.982, suggesting that for firms that post collateral, the probability of loan size rationing is reduced by just below 40 percentage points on average. As previously, the coefficient estimate for the number of collateral types is roughly half that of the collateral dummy, suggesting in the IV-probit case that the reduction in the likelihood of rationing for each additional asset type pledged is on average on the order of 18 percentage points. In sum, the linear-probability estimates of the effect of collateral on rationing not only remain statistically significant, but the implied economic magnitude of the effect substantially increases when estimated by IV-probit.

One final issue is whether pledging collateral also influences the magnitude of the rationed amount. In this complementary analysis, we estimate IV-tobit regressions by using as dependent variable the proportion of the applied-for amount rationed (one minus the proportion of the loan amount granted). Since the dependent variable is truncated between zero and one, the use of IV-tobit regression is more appropriate than alternative estimation methods. The results are reported in columns 3 and 4 of Table 27. The negative and statistically significant coefficient on *Collateral* in column 3 suggests that pledging collateral is associated not only with a reduction in the probability of experiencing loan size rationing, but also in the relative amount rationed. The negative and statistically significant coefficient on *#collateral types* suggests that an increase in the number of types of pledged assets also reduces the magnitude of the rationed amount. In sum, our finding provides direct empirical evidence of the role of collateral in mitigating both the probability of and the extent of loan size rationing.

6 CONCLUSION

There is a substantial body of theoretical work in the financial intermediation literature arguing that pledging collateral alleviates the information asymmetries that could lead to credit rationing. Yet, there is limited empirical research that establishes a direct link between posting collateral and credit rationing. The purpose of this study is to examine the empirical association between collateral and credit rationing in small business finance. To do that, we use survey data, which offers clean measures of credit rationing, and the focus of the analysis is on loan size rationing (the situation where a lender grants smaller loan amount than the borrower requested).

The sequential nature of the loan application/approval process, however, could become a potential source of selection bias if ignored. We estimate a three-step selection process to account for the potential selectivity problems. The findings show that the sequential loan demand, application and approval decisions are strongly related to one another. Prior literature also suggests that major loan terms are co-determined in credit contracting arrangements. To overcome the potential endogeneity bias arising from joint determination of loan terms, such as the pledged collateral and interest rate charged on the loans, we use instrumental variables estimation in the final loan size rationing models.

In benchmark regressions which do not account for potential selection and endogeneity bias, we find little evidence of an effect of collateral on rationing. In contrast, controlling for these issues we find consistent evidence of a direct empirical link between collateral and credit rationing, using several different IV estimators. More specifically, pledging collateral is associated with a reduction in the likelihood of experiencing loan-size credit rationing on the order of between 15 and 40 percentage points, depending on specification. Firms that pledge a large number of collateral types are also less likely to encounter credit rationing. The proportion of the loan amount rationed, defined as one less the proportion of the loan amount granted, is also observed to be negatively related to the incidence of collateral and the number of collateral types pledged.

REFERENCES

Anderson, T. W. and Rubin, H. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *Annals of Mathematical Statistics*, 20:46–63.

Ang, J. S., Lin, J. W., and Tyler, F. (1995). Evidence on the lack of separation between business and personal risks among small businesses. *Journal of Small Business Finance*, 4:197–210.

Atanasova, C. V. and Wilson, N. (2004). Disequilibrium in the UK corporate loan market. *Journal of Banking & Finance*, 28:595–614.

Avery, R. B., Bostic, R. W., and Samolyk, K. A. (1998). The role of personal wealth in small business finance. *Journal of Banking & Finance*, 22:1019–1061.

Baum, C. F., Schaffer, M. F., and Stillman, S. (2007). Enhanced routines for instrumental variables / generalized method of moments estimation and testing. *Stata Journal*, 7:465–506.

Becchetti, L., Garcia, M. M., and Trovato, G. (2011). Credit rationing and credit view: Empirical evidence from an ethical bank in Italy. *Journal of Money, Credit and Banking*, 43:1217–1245.

Benjamin, D. (1978). The use of collateral to enforce debt contracts. *Economic Inquiry*, 16:333–359.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S., and Miller, N. H. (2011a). Why do borrowers pledge collateral? New empirical evidence on the role of asymmetric information. *Journal of Financial Intermediation*, 20:55–70.

Berger, A. N., Frame, W. S., and Ioannidou, V. (2011b). Tests of ex ante versus ex post theories of collateral using private and public information. *Journal of Financial Economics*, 100:85–97.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., and Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76:237–269.

Berger, A. N. and Udell, G. F. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, 25:21–42.

Berger, A. N. and Udell, G. F. (1992). Some evidence on the empirical significance of credit rationing. *Journal of Political Economy*, 100:1047–1077.

Berger, A. N. and Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business*, 68:351–381.

Besanko, D. and Thakor, A. V. (1987). Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets. *International Economic Review*, 28:671–689.

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

Bester, H. (1987). The role of collateral in credit markets with imperfect information. *European Economic Review*, 31:887–899.

Beutler, T. and Grobéty, M. (2013). The collateral channel under imperfect debt enforcement. *Swiss National Bank Working Papers*.

Biais, B. . and Gollier, C. . (1997). Trade credit and credit rationing. *Review of Financial Studies*, 10:903–937.

Black, S. E. and Strahan, P. E. (2002). Entrepreneurship and bank credit availability. *Journal of Finance*, 57:2807–2833.

Blanchflower, D. G., Levine, P. B., and Zimmerman, D. J. (2003). Discrimination in the small-business credit market. *Review of Economics and Statistics*, 85:930–943.

Boden, R. J. J. and Nucci, A. R. (2000). On the survival prospects of men's and women's new business ventures. *Journal of Business Venturing*, 15:347–362.

Boot, A. W. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9:7–25.

Boot, A. W., Thakor, A. V., and Udell, G. F. (1991). Secured lending and default risk: Equilibrium analysis, policy implications and empirical results. *Economic Journal*, 101:458–472.

Brick, I. E. and Palia, D. (2007). Evidence of jointness in the terms of relationship lending. *Journal of Financial Intermediation*, 16:452–476.

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

Carter, S., Shaw, E., Lam, W., and Wilson, F. (2007). Gender, entrepreneurship, and bank lending: The criteria and processes used by bank loan officers in assessing applications. *Entrepreneurship Theory and Practice*, 31:427–444.

Cavalluzzo, K. and Wolken, J. (2005). Small business loan turndowns, personal wealth, and discrimination. *Journal of Small Business Finance*, 78:2153–2178.

Cavalluzzo, K. S., Cavalluzzo, L. C., and Wolken, J. D. (2002). Competition, small business financing, and discrimination: Evidence from a new survey. *Journal of Small Business Finance*, 75:641–679.

Cenni, S., Monferra, S., Salotti, V., Sangiorgi, M., and Torluccio, G. (2015). Credit rationing and relationship lending. Does firm size matter? *Journal of Banking & Finance*, 53:249–265.

Cerqueiro, G., Ongena, S., and Roszbach, K. (2016). Collateralization, bank loan rates, and monitoring. *Journal of Finance*, 71:1295–1322.

Chakraborty, A. and Hu, C. X. (2006). Lending relationships in line-of-credit and nonline-of-credit loans: Evidence from collateral use in small business. *Journal of Financial Intermediation*, 15:86–107.

Chakravarty, S. and Yilmazer, T. (2009). A multistage model of loans and the role of relationships. *Financial Management*, 38:781–816.

Chan, Y.-S. and Kanatas, G. (1985). Asymmetric valuation and the role of collateral in loan agreements. *Journal of Money, Credit and Banking*, 17:84–95.

Chan, Y.-S. and Thakor, A. V. (1987). Collateral and competitive equilibria with moral hazard and private information. *Journal of Finance*, 42:345–363.

Cheng, X. and Degryse, H. (2010). Information sharing and credit rationing: Evidence from the introduction of a public credit registry. *European Banking Center Discussion Paper No. 2010-07S*.

Coco, G. (2000). On the use of collateral. *Journal of Economic Surveys*, 14:191–214.

Cole, R. and Sokolyk, T. (2016). Who needs credit and who gets credit? evidence from the surveys of small business finances. *Journal of Financial Stability*, 24:46–60.

Cole, R. A. and Mehran, H. (2011). Gender and the availability of credit to privately held firms: Evidence from the surveys of small business finances. *FRB of New York Staff Report No. 383*.

Coleman, S. (2002). Borrowing patterns for small firms: A comparison by race and ethnicity. *Journal of Entrepreneurial Finance and Business Ventures*, 7:77–98.

Cowling, M. (1999). The incidence of loan collateralisation in small business lending contracts: Evidence from the UK. *Applied Economics Letters*, 6:291–293.

Cowling, M. (2010). The role of loan guarantee schemes in alleviating credit rationing in the uk. *Journal of Financial Stability*, 6:36–44.

Degryse, H. and Cayseele, P. V. (2000). Relationship lending within a bank-based system: Evidence from european small business data. *Journal of Financial Intermediation*, 9:90–109.

Diamond, D. W. (1989). Reputation acquisition in debt markets. *Journal of Political Economy*, 97:57–79.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, 99:689–721.

Drakos, K. and Giannakopoulos, N. (2011). On the determinants of credit rationing: Firm-level evidence from transition countries. *Journal of International Money and Finance*, 30:1773–1790.

Fairlie, R. W. and Robb, A. M. (2009). Gender differences in business performance: evidence from the characteristics of business owners survey. *Small Business Economics*, 33:375–395.

Freimer, M. and Gordon, M. J. (1965). Why bankers ration credit. *Quarterly Journal of Economics*, 79:397–416.

Gabriel, S. A. and Rosenthal, S. S. (1991). Credit rationing, race, and the mortgage market. *Journal of Urban Economics*, 29:371–379.

Han, L., Fraser, S., and Storey, D. J. (2009). Are good or bad borrowers discouraged from applying for loans? Evidence from US small business credit markets. *Journal of Banking & Finance*, 33:415–424.

Hansen, L. P., Heaton, J., and Yaron, A. (1996). Finite-sample properties of some alternative gmm estimators. *Journal of Business & Economic Statistics*, 14:262–280.

Harhoff, D. and Körting, T. (1998). Lending relationships in Germany - Empirical evidence from survey data. *Journal of Banking & Finance*, 22:1317–1353.

Haselman, R., Pistor, K., and Vig, V. (2010). How law affects lending. *Review of Financial Studies*, 23:549–580.

Hernández-Cánovas, G. and Martínez-Solano, P. (2006). Banking relationships: effects on debt terms for small spanish firms. *Journal of Small Business Management*, 44:315–333.

Hess, J. D. (1984). The use of collateral to enforce debt contracts: Profit maximization. *Economic Inquiry*, 24:349–356.

Inderst, R. and Müller, H. M. (2007). A lender-based theory of collateral. *Journal of Financial Economics*, 84:826–859.

Innes, R. D. (1990). Limited liability and incentive contracting with ex-ante choices. *Journal of Economic Theory*, 52:45–67.

Jaffee, D. M. and Modigliani, F. (1969). A theory and test of credit rationing. *American Economic Review*, 59:850–872.

Jaffee, D. M. and Russell, T. (1976). Imperfect information, uncertainty, and credit rationing. *Quarterly Journal of Economics*, 90:651–666.

Jappelli, T. (1990). Who is credit constrained in the U. S. economy? *Quarterly Journal of Economics*, 105:219–234.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102:2301–2326.

Jiménez, G., Salas, V., and Saurina, J. (2006). Determinants of collateral. *Journal of Financial Economics*, 81:255–282.

Kayhan, A. and Titman, S. (2007). Firms' histories and their capital structures. *Journal of Financial Economics*, 83:1–32.

Kirschenmann, K. (2016). Credit rationing in small firm-bank relationships. *Journal of Financial Intermediation*, 26:68–99.

Kjenstad, E. C., Su, X., and Zhang, L. (2002). Credit rationing by loan size: A synthesized model. *Quarterly Review of Economics and Finance*, 55:20–27.

Kleibergen, F. R. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133:97–126.

Kon, Y. and Storey, D. J. (2003). A theory of discouraged borrowers. *Small Business Economics*, 21:37–49.

Leeth, J. D. and Scott, J. A. (1989). The incidence of secured debt: Evidence from the small business community. *Journal of Financial and Quantitative Analysis*, 24:379–394.

Lehmann, E. and Neuberger, D. (2001). Do lending relationships matter? Evidence from survey data in Germany. *Journal of Economic Behavior and Organization*, 45:339–359.

Levenson, A. R. and Willard, K. L. (2000). Do firms get the financing they want? Measuring credit rationing experienced by small business in the US. *Small Business Economics*, 14:83–94.

Machauer, A. and Weber, M. (1998). Bank behavior based on internal credit ratings of borrowers. *Journal of Banking and Finance*, 22:1355–1383.

Manove, M., Padilla, A. J., and Pagano, M. (2001). Collateral versus project screening: A model of lazy banks. *RAND Journal of Economics*, 32:726–744.

Menkhoff, L., Neuberger, D., and Suwanaporn, C. (2006). Collateral-based lending in emerging markets: Evidence from Thailand. *Journal of Banking & Finance*, 30:1–21.

Mester, L. (1997). What's the point of credit scoring? *Journal of Political Economy*, pages 3–16.

Mester, L. J., Nakamura, L. I., and Renault, M. (2001). Checking accounts and bank monitoring. *FRB of Philadelphia Working Paper No. 01-3*.

Munnell, A., Tootell, G., Browne, L. E., and McEneaney, J. (1996). Mortgage lending in boston: Interpreting HMDA data. *Journal of Small Business Finance*, 86:25–53.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13:187–221.

Ogawa, K. and Suzuki, K. (2000). Demand for bank loans and investment under borrowing constraints: A panel study of Japanese firm data. *Journal of the Japanese and International Economies*, 14:1–21.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, 49:3–37.

Puri, M., Rocholl, J., and Steffen, S. (2011). Global retail lending in the aftermath of the us financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics*, 100:556–578.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, 11:159–206.

Rosa, P., Carter, S., and Hamilton, D. (1996). Gender as a determinant of small business performance: Insights from a British study. *Small Business Economics*, 8:463–478.

Schreft, S. L. and Villamil, A. P. (1992). Credit rationing by loan size in commercial loan markets. *Economic Review, Federal Reserve Bank of Richmond*, May:3–8.

Shen, C.-H. (2002). Credit rationing for bad companies in bad years: Evidence from bank loan transaction data. *Journal of Finance and Economics*, 7:261–278.

Steijvers, T. and Voordeckers, W. (2009). Collateral and credit rationing: A review of recent empirical studies as a guide for future research. *Journal of Economic Surveys*, 23:924–946.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71:393–410.

Stiglitz, J. E. and Weiss, A. (1987). Credit rationing with many borrowers. *American Economic Review*, 77:228–231.

Stock, J. H. and Wright, J. H. (2000). Gmm with weak identification. *Journal of Econometrics*, 68:1055–1096.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20:518–529.

Stock, J. H. and Yogo, M. (2005). Testing for weak instruments in linear iv regression. In Andrews, D. and Stock, J., editors, *Identification and Inference for Econometric Models: Essays in honor of Thomas Rothenberg*. Cambridge University Press, New York.

Voordeckers, W. and Steijvers, T. (2006). Business collateral and personal commitments in SME lending. *Journal of Banking & Finance*, 30:3067–3086.

Watson, H. (1984). Credit markets and borrower effort. *Southern Economic Journal*, 50:802–813.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, Massachusetts.

Appendix: First-stage results

Table 28. First stage regressions for endogenous variables

This table presents the IV-GMM first stage regression results for the included endogenous variables. *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; # *collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Column (1) reports results from the first stage for *Collateral*. Column (2) displays results from the first stage for *Interest rate*. Column (3) presents results from the first stage for # *collateral types*. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Collateral		*Interest rates*		*# collateral types*	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Existing collateral	.284***	.034	.037	.177	.544***	.079
% of banks tightening collateral	.002	.001	.031***	010	.006	.004
Float rate	.041*	.025	−.527***	150	.289***	.077
Treasury rate	.020	.016	.395***	102	−.002	.049
Log(Total sales)	.023	.015	−.195*	.110	.076*	.045
Lot(Number of employees)	−.003	.016	.031	.083	.019	.045
Log(Firm age)	−.017	.026	−.055	.154	−.041	.066
Profitability	−.072*	.043	−.324	.247	−.074	.132
Leverage	.000	.001	−.003	.004	.002	.002
Firm default history	−.0309	.070	.279	.457	.045	.188
Low diversification	−.032	.023	−.042	.175	−.148**	.072
Log(owner age)	−.122*	.072	−.753	.489	−.391**	.187
Asian ownership	−.102	.062	.070	.274	−.267**	.126
Black ownership	.049	.071	1.125*	.573	.128	.156
Hispanic ownership	.016	.056	.285	.309	−.077	.128
Female ownership	−.058**	.029	−.123	.185	.002	.087
Log(1 + Owner experience)	.009	.024	−.015	.207	.037	.073
Collage	.016	.023	−.110	.150	.049	.076
Primary owner share	.000	.000	.002	.003	.002	.001
Owner default history	.039	.055	.408	.324	.106	.137
Number of sources	−.008	.027	.022	.177	.081	.074
Log(1 + Relationship length)	−.013	.013	−.060	.079	−.016	.037
Log(1 + distance)	.002	.007	.123**	.055	−.001	.018
Referral	−.077	.057	.349	.369	−.158	.123

(Continued on next page)

Table 28. First stage regressions for endogenous variables (Continued)

	Collateral		*Interest rates*		*# collateral types*	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Previous loan	−.007	.037	.208	.216	−.040	.120
Primary bank	−.018	.025	.385∗∗	.189	−.087	.080
Log(Maturity)	.049∗∗∗	.013	−.140	.090	.088∗∗∗	.032
Amount / Total sales	.002∗∗	.0017	−.024∗∗∗	.006	.004	.003
Bank concentration	.014	.023	.423∗∗	.172	.067	.074
Metropolitan area	−.039	.036	.101	.270	−.112	.104
Demand Mill's ratio	.004	.231	−.480	1.509	.074	.609
Applied Mill's ratio	−.002	.224	1.077	1.713	.453	.623
Approved Mill's ratio	.043	.113	−.993	.687	−.041	.297
Loan type	YES		YES		YES	
Lender type	YES		YES		YES	
Organizational type	YES		YES		YES	
Industry	YES		YES		YES	
Region	YES		YES		YES	
Survey	YES		YES		YES	
N	2,340		2,340		2,340	