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*Ph.D Thesis*

# Essays in Empirical Corporate Finance

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To my wife, daughter, father, mother, siblings, and others who supported me through this extraordinary journey.

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## ABSTRACT

I use empirical methods to study the effects of firms' international activities and corporate governance on their operating performance, cost of funding, and credit risk. My studies provide novel evidence on the effects and implications of cross-border borrowing, foreign acquisitions, and governance on firms' financing decision and activities.

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# Chapter 1

# Preface

The primary interest of my doctoral studies is to analyze the effects of firms' international activities and corporate governance on their future policy, cost of funding, and credit risk. My Ph.D. thesis consists of three articles, split across three chapters, in the field of corporate finance and the preface summarizes the current and broad state of my research. I try to be both innovative and inventive when proposing research questions. I recycle old or use unique data sets, and emphasize nontrivial questions that occur in corporate finance. Then I propose answers with intuitive and appropriate examples.

Using empirical approaches, alone or with coauthors I address questions specifically focusing on the effects and implications of cross-border borrowing, foreign acquisitions, and corporate governance, "What motives drive cross-border borrowing?", "Do foreign block acquisitions increase target firms' credit risk?", and more over, "Does the quality of firms' corporate governance influence their future operating performance and enterprise value?" The answers lead to several explanations of the effects and implications of international activities of firms and governance on their financing decision and activities. I present a summary of each of the following papers.

Chapter 2 ***Why Do Firms Borrow from Foreign Banks?***, Umit Yilmaz

Chapter 3 ***Foreign Acquisition and Credit Risk:*** *Evidence from the U.S. CDS*

*Market*, Umit Yilmaz

Chapter 4 ***Does Corporate Governance Matter?*** *Evidence from the AGR Governance Rating*, Alberto Plazzi, Walter Torous, and Umit Yilmaz

## 1.1 Summary of Papers

My job market paper, *Why do firms borrow from foreign banks?*, studies the role of foreign banks in the U.S. syndicated loan market, with a particular focus on the motives that lead U.S. firms to borrow from lead arrangers. Cross-border syndicated loans cover a large component, around 10% of the total syndicated corporate loans in the U.S. In addition, there has been a lively debate in the literature regarding the pricing differences across countries (Carey and Nini, 2007; Berg et al., 2016). Given the increase in cross-border borrowing by the U.S. firms, I first start to investigate whether foreign loans are relatively cheaper than domestic loans by using Dealscan database. Interestingly, I find that firms that borrow from foreign lead arrangers pay around 16 basis points (bps) higher loan spreads compared to those that borrow from local banks, other things equal. The borrowing spread is robust to using various matching sample techniques to alleviate endogeneity concern. More importantly, it continues to hold when I use firm times year fixed effects, which indicates that firms borrowing in the same year from both domestic and foreign lenders pay significantly more for the foreign loans.

Given the evidence that foreign loans are relatively more expensive, a natural question is why would U.S. firms borrow from foreign banks and pay more? One possible explanation might be that borrowing from foreign banks allows firms to expand their operations overseas and establish a reputation in international markets. Consistent with this argument, I find that foreign bank borrowers experience a significant increase in their foreign income post borrowing. In addition to that, they are more likely to engage in cross-border M&As activities in the lenders' region after a foreign loan. Moreover, I find that loan spreads increase with the geographic and cultural distances between borrowers and foreign lenders. This result suggests that the higher the physical and cultural distances, the more the value of entering in a lending relation for the firm, the more it is willing to pay for the loan. An alternative explanation might be that domestic banks are credit constrained at the time of the foreign loan initiation. I conduct several tests but do not find any evidence supporting this claim. This paper provides novel insights on the motives that drive cross-border borrowing. In particular, the results suggest that global expansion of operations is an important reason why a firm chooses to borrow from a foreign bank.

My second sole-authored paper, *Foreign Acquisition and Credit Risk: Evidence from the U.S. CDS Market*, studies whether block acquisitions by foreign entities affect the U.S. target firms' credit risk as captured by their CDS. There are several competing theoretical predictions and empirical studies on the effects of foreign acquisitions on a firm corporate risk. For one, international diversification arguments suggest that foreign investors may shift investment toward more risky projects (Obstfeld, 1994; Acemoglu and Zilibotti, 1997; Faccio, Marchica, and Mura, 2011). In addition, if foreigners act as less effective monitors they may exacerbate agency problems (Moeller, Schlingemann, and Stulz, 2007). On the other hand, there is evidence that foreign ownership leads to more effective restructuring and efficiency in productivity, which in turn should decrease credit risk (Arnold and Javorcik, 2009; Chari, Chen, and Dominguez, 2012).

To address this question, I put together a cleaver dataset by merging M&A transaction information from SDC Thomson with CDS information from Markit, and balance sheet data from Compustat. I then test whether block acquisitions from foreign firms have an effect on the CDS of U.S. firms over and beyond that of firms acquired by U.S. firms, or other firms. Using an event-study type of approach, I find that the CDS premium on the former increases by a large 42 basis points over the 5-year following the acquisitions. This finding is robust to a wide array of controls and robustness tests and is consistent with a monitoring channel. More precisely, foreign owners might be less effective monitors due to information barriers.

Consistent with this idea, I find larger increases in CDS spreads when foreign owners are geographically and culturally more distant, and when they obtain majority control. The paper provides novel insights on the role of foreign investors on the domestic firms.

My third paper, *Does Corporate Governance Matter? Evidence from the AGR Governance Rating"*, which is co-authored with Alberto Plazzi and Walter Torous, investigates the relation between the quality of firms' corporate governance and their future operating performance as well as enterprise value. We use a relatively unexplored panel data on corporate governance ratings that are compiled by AGR (MSCI). The rating is based on the premise that a more accurate assessment of corporate governance can be formulated by taking the output of governance such as accounting quality and financial misreporting into account in addition to traditional governance inputs like board structure and anti-takeover provisions. By using a large panel data for the U.S. firms, we find that firms with better AGR scores exhibit better future operating performance (higher Tobin's Q, ROA, and sales growth), consistent with prior literature that uses metrics based on anti-takeover provisions. In addition to that, we investigate whether the beneficial effects of improved governance extend to both shareholders and bondholders. Our results indicate that an increase in the governance rating is associated with a decline in future CDS spreads and bond yields, and an increase in credit rating, which is consistent with an improvement in accounting transparency (Duffie and Lando, 2001; Yu, 2005). The findings suggest that better corporate governance is value enhancing for all claim-holders.

## 1.2 Ongoing & Future Projects

Additionally, I have two current projects, which are in different stages. The first work in progress, *The Wealth Effects of Cross-Border Acquisitions on Rival Firms*, studies the wealth effects of horizontal cross-border mergers and acquisitions on industry rivals, that is for firms that share the same 4-digit SIC code with the target companies. By using an event-study methodology, I find that average stock price reactions of industry rivals around deal announcements are significantly negative. The stock price effects increase with relatively high market-to-book ratio competitors, with larger acquirers, and with the differences in industry specialization between the acquirer and the target country consistent with a competitive hypothesis. Overall, the findings suggest that foreign acquisitions have strong competitive effects for the domestic rivals of target companies. Given the evidence on negative stock price reactions of industry rivals, I am next interested in exploring how cross-border M&As affect product market competition. International M&As comprise an important part of foreign direct investment (FDI). A fundamental question in the analysis of M&As is the potential trade-off between increased market power and efficiency gains. Increased market power creates net welfare losses, while efficiency gains lower costs and create net welfare gains.

Furthermore, I plan to extend my research on topics related to how international activities of banks affect cost of funding. For instance, the effects of foreign bank participation on lending to small and medium enterprises (SMEs) have been a controversial issue among academics and policymakers alike. The recent crisis has rekindled this debate and how foreign bank participations affect cost of funding for SME remains an important topic.

The thesis is structured as follows. Chapter 2, ***''Why Do Firms Borrow from Foreign Banks?''***, studies the role of foreign banks in the U.S. syndicated loan market, with a particular focus on the motives that lead U.S. firms to borrow from foreign banks. Chapter 3, ***''Foreign Acquisition and Credit Risk:** Evidence from the U.S. CDS Market''*, analyzes whether block acquisitions by foreign entities affect the U.S. target firms' credit risk by using an event-study type of approach. Chapter 4, ***''Does Corporate Governance Matter?** Evidence from the AGR Governance Rating''*, investigates whether corporate governance does have an effect on firm's valuation. There we use a relatively unexplored panel data on corporate governance ratings that are compiled by AGR. I hope that my research and contributions to lead to a better understanding of cross-border activities, governance, policy interactions them.

# Chapter 2

# Why Do Firms Borrow from Foreign Banks?

## 2.1 Introduction

In the United States, cross-border lending by foreign banks has increasingly become an important source of funding and comprises a significant component of total syndicated loans (De Haas and Van Horen, 2012; Berg et al., 2016). For instance, in 2007, international syndicated loans made up over 40% of all cross-border debt funding of U.S. borrowers. Despite the increasing importance of foreign loan supply in the U.S., little is known about the role of foreign banks and the terms of the syndicated loans they offer vis-à-vis domestic institutions. This paper fills this gap by studying the pricing and other features of foreign bank loans and exploring whether borrowing from foreign banks generates opportunities and economic consequences for a firm.

There has been a lively debate in the literature regarding the cost of foreign funding. Several studies have documented that loan spread increases with the physical distance between borrowers and lenders.[1] Distance-related information frictions between borrowers

[1] This research includes, among others, Brickley et al. (2003); Bharath et al. (2009); Agarwal and Hauswald (2010); Arena and Dewally (2012).

and lenders as a source of adverse selection and moral hazard affects contractual provisions, including loan amount, cost, and structure (Diamond, 1984; Beck et al., 2017). Classical theories suggest that lower asymmetric information benefits borrowers by reducing monitoring costs and lenders' exposure to credit risk, which in turn leads to more favorable loan terms. If global capital markets are not perfectly integrated, foreign funding is potentially more costly to obtain than domestic funding. However, differences in loan terms across countries have lead to an increase in cross-border lending activities. For instance, loan spreads on syndicated loans were about 30 basis points (bps) smaller in Europe than in the U.S. for otherwise similar loans and borrowers during the 1992-2002 period (Carey and Nini, 2007).[2] Thus, one might expect that U.S. borrowers can benefit from this pricing gap and borrow more cheaply from the European market. In the end, it is not clear whether foreign loans are relatively cheaper and, if not, what motives drive cross-border borrowing.

Using a large sample of term loans and revolving lines of credit originated between 1987 and 2016, I find that publicly traded non-financial U.S. firms that borrow from foreign lead arrangers pay higher loan spreads and (total) costs of borrowing compared to those that borrow from domestic lenders.[3] The effect holds for different loan types and cost components and is robust to controlling for a large set of borrower characteristics, loan features, and (high-dimensional) fixed effects. The most conservative specification implies that foreign lead arrangers charge, on average, 16 bps ($0.4 million per year) higher spread on their syndicated loans compared with local banks.

A potential explanation for this finding might be that foreign banks cater to different, and especially riskier clients than their domestic counterparts. Using various matching sample techniques, I show that the borrowing spread continues to hold, thereby alleviating endogeneity concerns. Moreover, I use a sample of firms that borrow from both domestic and foreign banks during the sample period or in a given year. Exploiting within-firm variation

[2] Berg et al. (2016) revisit pricing differences documented by Carey and Nini (2007) and show that the pricing gap has been eliminated partially by an increase in loan supply by cross-border lenders.

[3] I define "foreign" lead arrangers as those incorporated and located outside of the United States. A foreign branch of U.S. banks or a U.S. branch of foreign banks is not classified as a foreign lead arranger.

allows me to control for unobserved firm characteristics. By using firm×year fixed effects, I find that firms pay higher interest rate spreads on foreign bank loans relative to domestic bank loans in a given year.

Having shown that the differences in pricing terms do not reflect compensation for credit risk, a natural question is why would U.S. firms borrow from foreign banks that charge higher terms. One possible explanation might be that borrowing from foreign banks allows firms to expand their operations overseas and establish a reputation in international markets.[4] The informational disadvantage of a firm due to physical, linguistic, or cultural distances is one of the main obstacles that prevent them from doing business in foreign markets. Firms engaging in foreign market operations and activities need to overcome various barriers such as information costs, exchange-rate risks, and opposition against foreign entries.[5] For that reason, establishing a relationship with a foreign bank may help a firm to overcome the difficulties of entering and operating in a different business environment and culture. In line with this argument, I find that foreign bank borrowers experience a significant increase in foreign income after loan origination compared to domestic bank borrowers. In addition, they are also more likely to become multinational and participate in cross-border M&As in the lenders' region after loan initiation. These results suggest that the international expansion of businesses is an important reason why a firm borrows beyond borders. Another reason why firms establish relationships with foreign banks is to diversify their funding sources and thereby hedge against credit supply shock in their home countries (Jang, 2017).[6] Indeed, I find that foreign banks charge lower spreads and their share in total lending has increased during the 2008-2009 financial crisis.[7]

[4] For example, Chinese banks are recently increasing their lending in the U.S. syndicated loan markets as U.S. companies seek to penetrate into global markets. Dell Inc. said that it had developed relationships with Chinese banks, which made it easier to conduct business in China (Wong, 2012).

[5] See, e.g., Caves (1971); Hymer (1976); Sarkissian and Schill (2003); Chan et al. (2005); Dinc and Erel (2013).

[6] The recent 2008–2009 financial crisis provides a useful setting to test this prediction. A number of papers have documented that during the financial crisis, banks sharply cut their lending and increased loan interest rates to corporate sectors. For example, Ivashina and Scharfstein (2010) use data from the syndicated loan market to argue for evidence of a contraction in bank credit availability during the peak of the crisis. In addition, Santos (2010) uses data of bank loans from Dealscan to show that borrowers took smaller loans and paid higher loan spreads during the crisis period, which indirectly supports the claims on reduced credit availability.

[7] Another potential reason could be that firms are credit constrained in their local market and thereby forced to borrow from foreign banks with higher costs due to domestic credit supply contractions. To test for this competing channel, I investigate

Why do foreign banks charge higher rates in a competitive market such as that for syndicated loans? It might be costly for a bank to originate a loan to foreign borrowers. Doing so exposes the bank to significant adverse selection and moral hazard risks because the bank faces a greater degree of information asymmetry in screening and monitoring distant borrowers. Several studies have documented that the physical proximity of a firm with its lender is correlated with the effective monitoring and the existence of lending relationships.[8] Consequently, compared to local banks, foreign lenders find it harder to collect local information on the borrower, establish long-term relations, monitor the way funds are being used, and enforce contractual terms. This is indeed what I find in the data, as the loan spreads increase with geographic distance and cultural difference between foreign lenders and the borrowers holding everything else constant (including loan volume and firm size). I also document that loans from foreign lenders are significantly less likely to include financial covenants, suggesting that foreign lenders may engage in less on-going monitoring after loans are originated. Furthermore, I find that foreign lenders are less likely to participate in relationship lending and that they do not offer different terms for repeated interactions with a given borrower. While domestic banks base their pricing on the length of their relationship with the borrower, foreign banks have a more transaction-based pricing approach. These findings are consistent with an informational asymmetry and costly monitoring channel that arise across borders and exacerbated by distance.

In the last step of my analysis, I conduct a number of additional tests. I first show that U.S. lead arrangers also charge higher loan spreads when they lend to foreign firms suggesting that higher cost of borrowing is not U.S. market-specific. Second, I find that foreign banks charge lower spreads to U.S. multinational firms as collecting private information on those firms might be relatively easier compared to purely domestic firms. Third, the cost of borrowing is higher for non-rated firms, which are considered to be more opaque. Lastly, the

whether foreign banks charge higher loan terms when the credit market conditions are tightening. However, I do not find empirical evidence supporting this claim.

[8] See, e.g., Petersen and Rajan (2002); Brickley et al. (2003); Degryse and Ongena (2005); Agarwal and Hauswald (2010); Arena and Dewally (2012).

difference in loan terms based on lender types persist if I control for fraction of domestic bank participants in a given syndicate.

This paper contributes to the literature in several ways. First, it adds to the recent literature that tests cross-country differences in loan pricing (see, e.g., Carey and Nini, 2007; Berg et al., 2016). Carey and Nini (2007) document that interest rate spreads on syndicated loans were about 30 bps smaller in Europe than in the U.S. during the 1992 to 2002 period. However, Berg et al. (2016) revisit the pricing puzzle documented by Carey and Nini (2007) and show that a fall in the pricing differences between the U.S. and European syndicated loans has been accompanied by an increase in institutional investor participation (primarily for non-investment-grade borrowers) and by an increase in cross-border activity (primarily for investment-grade borrowers). To the best of my knowledge, this paper is the first to study how cross-border lenders set the price and non-price terms of the debt financing they provide in the U.S. syndicated loan market. My results suggest that foreign lead arrangers charge higher spreads than domestic arrangers for otherwise similar loans and borrowers.

Second, this study extends the literature on the determinants and implications of cross-border borrowing (see, e.g., Houston et al., 2017; Jang, 2017). Houston et al. (2017) find that firm-level foreign assets are an important mechanism in reducing the boundary between borrowers and lenders suggesting that firms with foreign assets are more likely to select a foreign bank and that the corresponding loans have better pricing terms. Jang (2017) documents that U.S. multinationals are more likely to borrow from foreign banks with better pricing terms. She also shows that multinationals have benefited from greater funding flexibility during the recent financial crisis and reduced domestic investment less than domestic firms did. This paper provides new insights on the motives that drive borrowing from foreign banks. In particular, the results suggest that global expansion of operations is an important reason why a firm borrows beyond borders.

Finally, it adds to an extensive literature on the importance of geographic and cultural distance in lending and pricing activities. Several studies have documented that the geographical distance of a firm with its lender affects information gathering and processing, monitoring, and the existence of lending relationships.[9] However, those studies focus on the local effects mostly within a country or a region. Given that financial frictions are more severe and enforcement of debt contracts is more difficult across international borders, the distance would matter more in global lending decisions. I contribute to this literature by documenting how physical distance influences loan pricing in an international setting. In addition, Giannetti and Yafeh (2012) show that loan spreads increase with the 'cultural distance' between the lead arrangers and the borrowers. They also show that having a local subsidiary in the country of the borrower mitigates, but does not eliminate the effect of 'cultural distance'. Domestic banks share a culture with local firms, and they are familiar with the regulatory conditions and accounting rules that govern a local firm. They may also have a better understanding of local economic and political risks, and in the event of default may have a better understanding of the adjudication process. Consistent with this idea, I show that cultural ties ease information transfer and influence loan pricing.

The remainder of the paper is structured as follows. Section 2 discusses the economic mechanism and empirical predictions. Section 3 describes the data and presents summary statistics. Section 4 describes the methodology and presents the empirical results. Section 5 examines the motives beyond borrowing from foreign banks and explores the ex-post performance of loans in the data. Section 6 examines the reasons why foreign banks charge higher loan terms. Section 7 provides further analyses. Section 8 concludes.

## 2.2 Economic Mechanism and Empirical Predictions

While financial markets have become increasingly interconnected, several studies show that information asymmetry still matters in behavioral, economic, and financial outcomes. Diamond (1984) and James (1987), among many others, argue that banks mitigate problems

[9] This research includes, among others, Petersen and Rajan (2002); Brickley et al. (2003); Degryse and Ongena (2005); Bharath et al. (2009); Agarwal and Hauswald (2010); Arena and Dewally (2012).

of asymmetric information. Degryse and Ongena (2005) and Petersen and Rajan (2002) focus on the effect of distance on information costs and lending, and Hadlock and James (2002) note that some firms may choose to issue in higher-cost markets in which their quality is not clearly revealed. Taken together, the body of such work suggests that the identity of lenders may matter, that is, the same borrower might pay different spreads to one set of lenders than to another because of differences in lenders' information about the borrower's credit quality. Besides, foreign lenders have different renegotiation policies and reputations due to differences in home market law, regulation, and financial system structure. A lender that chooses renegotiation policies that are optimal for its domestic market may essentially offer a different loan product in the eyes of borrowers than a lender from another nation, and thus loan spreads may differ with lender nationality.

Bank lenders often rely on a mix of "hard" and "soft" information when granting and pricing credit.[10] While hard information, such as financial statements and credit records, is often readily available, soft information is typically more costly to obtain. Several studies highlight how information asymmetries generate the need for collecting soft information.[11] However, the ability of lenders to mitigate information problems depends on the costs of gathering and processing private information. Physical proximity, for instance, makes it easier for lenders to collect private information about local borrowers and to evaluate a borrower's creditworthiness. Indeed, a large banking literature has documented that the geographic proximity of a firm with its lender is correlated with the effective monitoring and the existence of lending relationships (see, e.g., Petersen and Rajan, 2002; Brickley et al., 2003; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Arena and Dewally, 2012). For instance, Agarwal and Hauswald (2010) find that borrower proximity facilitates the bank's collection of soft private information, which the lender uses to create an adverse selection problem for competitors, allowing the lender to carve out a local captive market. Mian (2006)

[10] Soft information is a type of information that is hard to communicate to others, let alone capture in written documents, whereas hard information is a type of information that is quantitative, is easy to store, and can be transmitted in impersonal ways (see, Petersen and Rajan, 2002).

[11] This research includes, among others, Petersen and Rajan (1994); Houston and James (1996); Petersen and Rajan (2002); Carey and Nini (2007).

suggests that greater distance between a foreign bank's headquarters and their local branches not only decreases the incentives of a loan officer to collect soft information but also makes it more costly to produce and communicate such information. In a local setting, Degryse and Ongena (2005) highlight the various ways in which distance, transactions and monitoring costs, and competition affect loan pricing.[12] Thus, the asymmetric information problem that arises due to the physical distance between borrowers and lenders affects contractual provisions, including loan amount, cost, and structure.

In addition to problems of information asymmetry, the institutional environment, which includes the competitive environment and the legal and regulatory environment, may also affect a borrower's choice of lender. Domestic banks share a culture with local firms, and they are familiar with the regulatory conditions and accounting rules that govern a domestic firm. These banks may also have a better understanding of local economic and political risks, and in the event of default may have a better understanding of the adjudication process. In line with this view, Giannetti and Yafeh (2012) find that loan spreads increase with the 'cultural distance' between the lead arrangers and the borrowers. Most importantly, they show that having a local subsidiary in the country of the borrower mitigates, but does not eliminate the effect of 'cultural distance'.

Carey and Nini (2007) examine the home bias in syndicated lending and are puzzled by unexplained pricing discrepancies between the U.S. and European markets. More specifically, they find that loan spreads in the corporate syndicated loan market, on average, were about 30 bps smaller in Europe during the 1992 to 2002 period, which cannot be explained by differences in lender, borrower or loan characteristics. This finding is puzzling as financial theory suggests that arbitrage opportunities should be competed away unless prevented by market frictions. One avenue might focus on why borrowers do not cross borders. The authors suggest that issuing out of the home market is costly, potentially explaining why

[12] Focusing on a dataset of 15,000 bank loans from a large Belgian bank, Degryse and Ongena (2005) show that loan rates decrease with the distance between the firm and the lending bank, and increase with the distance between the firm and competing banks. They conclude that borrower-borne transportation costs enable lenders to price discriminate based on distance.

so few U.S. firms issue in Europe, which is an important element of the puzzle. Berg et al. (2016) revisit the pricing puzzle documented by Carey and Nini (2007), and extend the sample to the 1992-2014 period. Their results indicate that variations in the pricing difference between the U.S. and European syndicated loans are accompanied by variation in institutional investor flows in the below investment-grade market and by foreign bank lending flows in the investment-grade market. While Carey and Nini (2007) provided some evidence that cross-border activity is limited over the 1992–2002 period, they document that cross-border activity in the syndicated loan market has significantly increased over time, particularly with respect to foreign banks supplying loans in the U.S. market. Their results suggest that foreign bank supply is highly correlated with the fall in pricing differential between the U.S. and European markets, in particular for investment-grade borrowers.

These economic mechanisms lead to the following empirical predictions. First, foreign loans, on average, carry a higher spread compared to domestic loans. Second, foreign banks differ in setting the non-price terms of the debt financing they provide compared to their domestic counterparts. Third, the higher the physical and cultural distance between foreign lenders and borrowers, the greater the cost of borrowing. Finally, foreign bank borrowers operate differently than domestic bank borrowers.

## 2.3 Data and Descriptive Statistics

I now describe my sample construction and provide summary statistics on borrowers and loans in my data.

### 2.3.1 Data

My sample consists of term loans and revolving lines of credits in the Thomson Reuters Loan Pricing Corporation's (LPC) Dealscan database.[13] For the typical loan, Dealscan

[13] I refer to Carey et al. (1998) and Chava and Roberts (2008) for a detailed description of the Dealscan database.

includes the name and location of the borrower and the names of all of the lenders and their role in the loan contract at inception. Additionally, specific loan information includes the loan amount, date of loan inception, projected maturity, loan type and purpose, and pricing. I use the loan facility (or loan tranche) as the unit of analysis, for the borrower-lender relationship is facility specific.[14] I exclude loans taken out by non-U.S. firms, financial firms, and utilities (SIC codes 6000-6999 and 4900-4999, respectively), as well as those that mature in less than a year.[15] In addition, I exclude loans denominated in foreign currencies.[16] I also augment the Dealscan loan-level data by merging it with the comprehensive total cost of borrowing measure over the period 1987 to 2011 from Berg et al. (2016).

I restrict the sample of institutions to only those classified as "banks" in Dealscan. The empirical objective of this paper is to examine the pricing effects of loans originated by foreign lead arrangers.[17] I only focus on deals where I can identify a single lead arranger. Following Bharath et al. (2009) and Berg et al. (2016), I define a bank to be a lead lender if either the "Lead Arranger Credit" is equal to "Yes" in Dealscan or the lender role specified is either that of an "Agent", "Administrative Agent", "Arranger", "Lead Bank" or "Sole Lender". I define "foreign" banks as those located outside the countries of the borrowers. That is, I classify lenders incorporated outside of the United States as "foreign" banks based on the information on the nationality of each lender provided by Dealscan. A foreign branch of U.S.

[14] Each loan reported in Dealscan contains one or multiple facilities. The final sample includes 25,111 loan facilities associated with 18,706 deals. Within the same loan deal, each loan facility can have different starting dates, maturity, amount, and loan type. A loan-facility analysis is appropriate as multiple loan facilities in the same loan deal cannot be treated as fully dependent observations (e.g., simply adding facilities and ignoring their differences, may therefore introduce a bias in the estimates). However, analysis with the data aggregated at the deal level does not influence the main results of this paper.

[15] This paper focuses only on publicly traded U.S. firms for the following reasons. First, the majority of deals in the Dealscan database (around 60%) are extended to U.S. firms. Second, since I have detailed information on borrowers in the U.S., I am able to examine the effects of individual borrower characteristics, which turns out to be crucial to the results. Finally, there has been an increase in loan supply by foreign banks to the U.S. firms but not the other way around.

[16] In untabulated results, I find that the main results of the paper become stronger when I include non-USD-denominated loans in the sample. There are 256 total loans (85 foreign-led and 171 domestic-led) extended to 117 publicly traded U.S. firms during the sample period. Some firms might have an incentive to receive loans denominated in a foreign currency to hedge their foreign currency risk. Therefore, restricting the sample to US-dollar-denominated loans allows me to control for the demand of firms that borrow in foreign currencies for hedging purposes.

[17] In this paper, I only focus on lead arrangers since these institutions initiate, arrange, and manage the loan and have the screening and monitoring responsibilities. As a lead lender, banks bear the monitoring cost and need to hold a higher share of the loans on their balance sheet, thus, face more reputation damage if the borrower defaults on the loan (Irani and Meisenzahl, 2017; Gopalan et al., 2011). Consequently, it is the lead arranger that is primarily associated with the loan and most likely benefits or suffers from lending to a foreign borrower.

banks or a U.S. branch of foreign banks is not classified as a foreign lender.[18]

Using the Dealscan-Compustat Linking Database of Chava and Roberts (2008), I collect annual financial statement information for each borrower from Compustat. I supplement Dealscan data with (i) annual borrower financials (as of the most recent fiscal year end preceding the loan date) from Compustat, (ii) daily stock price information from the Center for Research in Security Prices (CRSP), and (iii) mergers and acquisitions (M&As) from SDC database. I require non-missing data on firm and loan characteristics used in my loan pricing models. I provide detailed variable definitions in Appendix C.

### 2.3.2 Descriptive statistics

The merged sample covers the time period 1987 to 2016. I winsorize all continuous and unbounded variables at the 1% and 99% level to mitigate the effects of outliers. The final data set contains 25,111 loans (2,115 foreign-led and 22,996 domestic-led) originated by 1,062 banks (184 foreign and 878 domestic) to 5,383 publicly traded U.S. borrowers between 1987 and 2016.[19]

Figure 2.1 shows the total number of cross-border and domestic loans issued by U.S. borrowers over the period 1987-2016. The loans made by foreign banks indicate a small surge in 1996 and a more pronounced surge in 2007. However, we observe a huge decline in loan numbers extended by foreign lead arrangers during the 2008-2009 financial crisis. For domestic loans, we note a dramatic increase in loan numbers during 1995-1996 and a decline during the recent financial crisis. Figure 2.2 instead shows the total value of loans by lender type. The loan volume made by foreign banks indicates a small surge in 1996 and a more pronounced surge in 2007. A huge decline in the amount originated by foreign lead arrangers can be observed during the recent global financial crisis. We also observe a dramatic increase

[18] Such an approach is extremely conservative, for it treats U.S. branches of foreign banks as U.S. banks.

[19] Appendix Table A1 presents information by country of origin on the number and value of loans to the U.S. firms. The top five foreign countries whose banks lend to the U.S. firms over the period 1987-2016 are: Canada, Switzerland, France, Germany, and the United Kingdom.

in domestic loan volume during 1995-1996 and a decline during the recent financial crisis.[20]

Table 2.1 provides summary statistics by comparing the characteristics of loans extended by foreign lead arrangers with those that had domestic leads. The mean spread over LIBOR of syndicated loans differs enormously between the two samples. The average loan in the foreign bank sample has a relatively higher loan spread (232 bps vs. 192 bps) and a higher total cost of borrowing (188 bps vs. 145 bps). The mean difference in loan spreads between the two samples is about 41 bps and statistically significant.[21] Their maturities are also longer by around 7 months (57 months vs. 50 months). The facility amount for foreign loans is relatively skewed towards small loans with a mean of USD 235 million and a median of USD 100 million whereas the facility amount for domestic loans is relatively skewed towards large loans with a mean of USD 252 million and a median of USD 100 million. In addition, foreign bank loans are more likely to be secured (91% vs. 85%) and less likely to feature financial covenants (49% vs. 56%). Moreover, foreign banks are less likely to be involved in repeated interactions with a given borrower (33% vs. 38%). This indicates that domestic banks base their loan pricing on the length of their relationship with the borrower, while foreign banks have a more transaction-based pricing approach, relying on borrower credit ratings and collateral pledges. Overall, compared to domestic bank loans, foreign bank loans are significantly smaller, have higher interest rates, have longer maturities, are more likely to be secured, and are less likely to include financial covenants and performance pricing. These results provide initial confirmation that foreign lenders differ in setting the price and non-price terms of the debt financing they provide.

When we turn to borrowers characteristics, Table 2.1 shows that the average borrower in the foreign bank sample has total assets of USD 2.54 billion, a leverage ratio of 35%, a profitability of 12%, tangibility of 35%, a current ratio of 187%, a market-to-book ratio of 173%, and a return volatility of 0.03. About 12% of foreign loans belong to borrowers with an investment-grade rating, while 46% of borrowers have no rating at all. On the other hand,

[20] Appendix Figure A1 shows the share of foreign banks in total bank lending over the years.

[21] Figure 2.3 shows the difference in loan spread between foreign and domestic banks over the period 1987-2016.

the average borrower in the domestic bank sample has total assets of USD 2.52 billion, a leverage ratio of 30%, a profitability of 12%, tangibility of 30%, a current ratio of 203%, a market-to-book ratio of 172%, and a return volatility of 0.03. About 20% of domestic bank loans belong to borrowers with an investment-grade rating, while 59% of borrowers have no rating at all. Overall, firms borrowing from foreign banks are rated firms with more leverage, tangible assets, and 'weaker' bank-lending relationships. These results are consistent with the asymmetric information problems and costly monitoring that arise across borders and exacerbated by distance.

What determines the choice of borrowing from a foreign bank? I next turn to a multivariate analysis by investigating factors that influence the decision of borrowers to choose a foreign bank lender, including firm demand driven considerations. To do so, I estimate a linear probability model predicting whether a lead lender is a foreign or domestic bank. The independent variables include firm-specific characteristics and loan facility features. Firm-level characteristics include *Log(total_assets), Leverage, Profitability, Tangibility, Current ratio, Market-to-book,* and *Stock volatility.* The regression also includes S&P credit rating fixed effects and industry fixed effects at the two-digit SIC industry level. Loan characteristics include *Log(facility amount), Log(maturity), Secured, Financial covenant,* and *Performance pricing*, as well as deal purpose and loan facility type fixed effects. Standard errors are clustered at the firm level.

The results in Table 2.2 show that firm size is consistently associated with a significantly higher probability of borrowing from a foreign lender. Higher leverage and market-to-book ratio are positively associated with the likelihood of borrowing from a foreign bank but the coefficient is not significant when I include loan features or firm fixed effects. Overall, these results suggest that except for size there are no significant differences in the demand side or ex-ante selection among the firms that use foreign vs. domestic banks.

## 2.4 Foreign Banks and Loan Pricing

Univariate comparisons in Table 2.1 suggest significant differences in both price and non-price terms of foreign versus domestic bank loans. Foreign lead arrangers, for example, charge significantly higher interest rates. Some of these differences in contract terms are likely due to differences in the characteristics of firms that borrow from foreign versus domestic lenders. In particular, as we just saw, firms that borrow from foreign arrangers are relatively larger and rated firms. The question I ask in this section is whether differences in contract terms persist once I control for firm characteristics. In other words, when firms that are similar on observable characteristics borrow from different types of lenders, do they obtain similar or different terms? I use three approaches to identify the effect of foreign banks on outcome variables related to loan pricing. First, I apply fixed effects regressions with lagged firm controls to isolate the effect of foreign banks on loan pricing. Second, I use different matching estimators to evaluate the average treatment effect of foreign banks on loan pricing. Finally, I explore within-firm variation by using a sample of firms that borrow from both domestic and foreign banks during the sample period.

### 2.4.1 Fixed-Effects Regression

To formally study the relation between foreign lead arrangers and loan pricing, I estimate the following regression model:

$$\begin{aligned} Log(Spread) = {} & \beta_0 + \beta_1\, Foreign(0/1) + \sum_i \beta_i\, BorrowerCharateristic_i \\ & + \sum_j \beta_j\, LoanCharateristic_j + \sum_k \beta_k\, FixedEffect_k \end{aligned} \tag{2.1}$$

The dependent variable $Log(Spread)$ is the logarithm of different measures for the loan pricing.[22] I use the logarithm of all-in-drawn loan spread over LIBOR as the main measure of loan pricing throughout the most part of my analysis. As an alternative measure, I use the logarithm of the total cost of borrowing (TCB) measure of Berg et al. (2016), which reflects the option characteristics of bank loans and takes the likelihood of exercising these options as well as the different fees into account.[23]

The variable of interest is the $Foreign(0/1)$, which is a dummy variable equal to one if the loan is extended by a foreign lead arranger, zero otherwise. Thus, the main coefficient of interest is $\beta_1$, which captures the differences between foreign and domestic loan spreads holding firm and borrower characteristics constant.

I add loan and borrower characteristics that directly affect the loan pricing or simultaneously drive lender choice and loan pricing. On the loan level, I follow the literature and control for loan size, maturity, number of lenders, whether the loan is secured, has financial covenants, prime as base rate, or performance pricing. On the firm level, I control for firm size, leverage, profitability, tangibility, the current ratio, the market-to-book ratio, and return volatility. All firm characteristics are at the latest fiscal period that ended prior to loan start date to avoid an overlap with the period of loan issuance. Throughout most of my analysis and following the literature on loan pricing, $FixedEffect_k$ is a vector of loan type, loan purpose, rating, industry, and year dummies.

I estimate the above regression model with multi-level fixed effects by applying the feasible and computationally efficient estimator of Correia (2016). Importantly, the estimator eliminates singleton observations which typically arise in a model with multilevel fixed effects and which might overstate statistical significance. As loans to the same firm might be correlated with each other, I adjust standard errors for within firm-clusters (see, e.g., Petersen, 2009; Valta, 2012; Hertzel and Officer, 2012).

[22] I use the logarithm to account for skewness in the data. My results remain qualitatively unchanged if I use the level instead.
[23] Appendix B provides detailed information on the total cost of borrowing (TCB) measure of Berg et al. (2016).

#### 2.4.1.1 Foreign banks and interest rate

Table 2.3 reports the coefficient estimates of model (1) for loan spread and total cost of borrowing with the foreign arranger dummy as the key explanatory variable. In the first column, I report my main regression specification-controlling for loan features and borrower characteristics, including rating, industry, year, loan type and purpose fixed effects, and standard errors clustered at the firm level. I find that the coefficient of the foreign arranger dummy is positive and highly statistically significant (coefficient: 0.081, t-statistic: 4.47). The economic magnitude of this coefficient is about 16 bps ($8.1\% * 191.60 \approx 16$). To alleviate concerns that the time fixed-effect does not appropriately account for industry dynamics, I include industry-year fixed effects. The results remain virtually the same (coefficient 0.084, t-statistic: 4.70). I also replace rating and industry fixed effects by firm fixed effects in my baseline specification to control for firm-specific time-invariant unobservables, which yields slightly a lower point estimate (coefficient: 0.058, t-statistic: 2.48). In addition, I look at firms that borrow from both domestic and foreign banks in a given year by using firm×year fixed effects. The magnitude remain virtually the same (coefficient 0.081, t-statistic: 1.80), suggesting that firms pay higher interest rate spreads on foreign bank loans relative to domestic bank loans in a given year. The coefficients of foreign arranger dummy are positive and highly statistically significant for the total cost of borrowing in all specifications.[24]

Overall, the coefficient estimate is similar across most of the specifications. The results indicate that firms that borrow from foreign lead arrangers pay, on average, 16 bps higher interest rates on the loans than local bank borrowers do, controlling for firm and loan characteristics. Thus, these firms pay, on average, \$0.4 million per year ($0.16\% * 251.52 \approx 0.4$) higher loan terms compared to firms that borrow from domestic banks.

The estimates of the control variables have the expected sign. The coefficient of the loan

[24] I also investigate the impact of loans extended by foreign banks on individual fee types in Appendix Table A2. On the fee level, I find a statistically significant positive impact of foreign banks on commitment fees (i.e. fees on unused loan commitments). I do not find strong evidence between foreign lead arranger and upfront fees or the facility fee. Moreover, I study the effect of foreign banks on loan pricing in a subsample analysis based on rating groups. The results in Appendix Table A3 show that foreign banks charge higher spreads in particular for non-rated borrowers, which are considered to be more opaque firms.

amount is negative and statistically significant which suggests that firms with larger financing needs receive cheaper funding due to positive economies of scale. Surprisingly, secured loans have significantly higher loan spreads. As discussed by Hertzel and Officer (2012), this is a common finding in nearly all empirical studies using Dealscan data. It is the result of this variable capturing variation in credit risk that is not picked up by the other control variables. The coefficient of the prime base rate dummy is on average negative and weakly statistically significant which suggests that loans which are based on the U.S. prime rate have lower borrowing costs compared to loans which are tied to LIBOR. In line with the existing literature, the loan spread is higher for loans with shorter maturities, loans with less number of lenders, loans with financial covenants, and loans which feature a performance pricing schedule. Moreover, loan spread is significantly higher for borrowers with high leverage and stock return volatility, consistent with structural models of credit risk (see, e.g., Black and Scholes, 1973; Merton, 1974). Borrowers with higher market-to-book ratios (i.e. higher growth opportunities), on the other hand, face lower loan spreads.

As stated by Berg et al. (2016), loan contracts differ substantially with respect to embedded option characteristics. In particular, the spread of term loans and credit lines are fundamentally different objects-in term loan contracts, borrowers have to pay the spread on a regular basis, while in credit line contracts, borrowers pay the spread only when they decide to exercise the option to draw on the credit line. I test whether there are significant differences between the effect of foreign arrangers on term loans and credit lines. Therefore, I restrict my sample to loans that I can identify as either of the two loan types. The results are reported in Appendix Table A4. I find evidence for higher TCB and upfront fees for credit lines of foreign banks' borrowers compared to term loans. I do not find that loan spreads and facility fees are significantly different between the two loan types. I also perform F-tests to test whether the effect of foreign banks is also positive and significant for credit lines overall. Indeed, I find that foreign arranger dummy positively affects all measures except for facility fees of borrowing costs for credit lines.

#### 2.4.1.2 Foreign banks and non-price contract terms

While I already touched on how differences in non-price terms explain some of the difference in interest rates between foreign and domestic loans, I now turn to a more systematic examination of the non-price terms.

Non-price terms affect the lender's ability to obtain a fair return on the loan; these include the loan amount, its maturity, and whether the loan is secured or guaranteed by a third party. Thus, an effect of foreign banks on contracting costs should be reflected also in more restrictive non-price loan terms. Table 2.4 reports the results of OLS regressions of various non-price terms on lender type dummies. The results show that foreign banks have a positive impact on the probability that the loan is secured (columns 1 and 2) and on the loan maturity (columns 5 and 6). These effects are statistically significant at 1% level. The results in columns (3) and (4) show that loans from foreign lenders are significantly less likely to include financial covenants, suggesting that foreign lenders may engage in less on-going monitoring after loans are originated. The results in columns (7) and (8) indicate that foreign lead arrangers have a negative impact on the loan amount, while the effect is statistically significant only when I include firm fixed effects.

### 2.4.2 Matched Sample Analyses

Given the differences between foreign and domestic bank borrowers, I address the potential concern that firms access to foreign lending markets occurs because of differences in characteristics of the two groups. To address this self-selection issue, I employ several matching methods to match loans extended to foreign bank borrowers to comparable loans extended in the same quarter to domestic bank borrowers with similar observable characteristics.

The first class of matching estimators I use is coarsened exact matching (CEM) (Iacus et al., 2012). CEM is a matching method where the balance between treated and control group is chosen ex-ante through coarsening. The CEM algorithm coarsens variables into groups and assigns them the same numerical value. Then, exact matching is applied to the coarsened data to determine matches and prune unmatched observations. Only uncoarsened values of the matched data are then used in regressions. The CEM procedure thereby automatically restricts the matched data to areas of common empirical support.

As a first step, I calculate the imbalance between treated and untreated observations by computing the $\mathcal{L}_1$ distance which is a measure of imbalance bounded between 0 (perfect balance) and 1 (complete separation). Appendix Table A5 shows the imbalance and the differences in mean and median between treated and control groups before and after CEM. The imbalance is largest with respect to total assets, leverage, market-to-book ratio, and return volatility. I first apply the CEM algorithm on total assets and leverage and use the resulting matches in my baseline regressions specification. Table 2.5 shows the regression results on the coarsened-exact matched samples. I find a significant positive effect of foreign banks on loan spreads (coefficient: 0.079, t-statistic: 4.39) and the total cost of borrowing (coefficient: 0.060, t-statistic: 3.45). I then apply the CEM algorithm on total assets, leverage, profitability, market-to-book, current ratio, and return volatility to further reduce the imbalance. The results continue to hold and they are quantitatively higher by magnitude.

The second class of matching estimators belongs to approximate matching methods which specify some metric to find a control group that is close to the treated observations. I apply two commonly used approximate matching methods as robustness checks-nearest-neighbor matching (NNM) and propensity score matching (PSM). In both cases, I am interested in the average treatment effect on the treated (ATET) of firms borrowed from foreign banks.

NNM uses some distance metric between covariate patterns of treated firms to find the closest matches among control firms. Since using more than one continuous covariate in NNM introduces a large sample bias, I employ the bias-adjustment proposed by Abadie and Imbens (2006, 2011). Panel A of Table 2.6 shows the ATET for different NNM specifications. I match on borrower characteristics in all models and find a positive significant coefficient on foreign bank dummy for 1 or 10 neighbors. Since there might also be an endogeneity problem with respect to the loans firms issue, I also match on loan features in addition to firm characteristics. The results are statistically significant and consistent with the previous analyses across all models. When I also match on loan features, the magnitudes are similar to previous point estimates.

PSM matches on the estimated probability of being treated (propensity score). Estimating the ATET only requires finding matches for the treated observations. Since the typical derivative-based standard error estimators cannot be used in this case, I rely on the non-parametric method derived in Abadie and Imbens (2016) to compute standard errors. Again, I apply different models-matching on firm characteristics only, matching on loan features and firm characteristics, using different number of neighbors. I find a statistically significant positive coefficient on the foreign bank dummy as shown in Panel B of Table 2.6. In addition, the results for the PSM are quantitatively higher by magnitude compared to the previous analyses.

### 2.4.3 Exploring within-firm variation

To understand whether differences in pricing terms between domestic and foreign bank loans are solely due to their different clienteles or also due to the use of different lending information, I use a sample of firms that borrow from both domestic and foreign banks during the sample period. That is, I hold the clientele constant and compare the pricing terms of domestic and foreign bank loans to the same firm. Exploiting within-firm variation allows us to control for unobserved firm characteristics. To this end, I restrict the analysis to a sub-sample of loans to firms that receive a new loan from at least one foreign and one domestic bank during the sample period. The restriction results in a sub-sample of 5,715 loans to 632 firms.

The results in Table 2.7 show that foreign banks charge higher loan spreads compared to domestic banks for the same firms. These results suggest that domestic and foreign banks could cater to the same clientele but using different lending information.

## 2.5 What drives borrowing from foreign banks?

The evidence so far shows that compared to domestic banks, foreign banks charge higher loan spreads. Most importantly, I show that the differences in pricing terms are not likely to be driven by the riskiness of borrowers. These results raise the question of why U.S. firms borrow from foreign banks that charge higher loan terms. To help shed light on this question, this section focuses on the motives driving cross-border borrowing and changes in borrowers' policies and operations after the loan initiation.

### 2.5.1 Expanding operations overseas and diversifying funding sources

While globalization has melted national borders, there are still several difficulties to operate in a different business environment and culture (see, e.g., Caves, 1971; Hymer, 1976; Sarkissian and Schill, 2003; Chan et al., 2005; Dinc and Erel, 2013). Firms value relationships with foreign banks that make it easier for them to enter and conduct business in an unknown market as they are typically better informed about their domestic market. To the extent that funding from foreign banks improves a firm's access to the international markets, I conjecture that borrowers should increase their overseas operations and incomes. Consistent with this prediction, the results in Panel A of Table 2.8 show that foreign banks are significantly associated with an increase in borrowers' foreign incomes. Most noteworthy, I find that foreign bank borrowers are more likely to become multinational and participate in cross-border takeovers in the lenders' region after loan initiation. These results suggest that global expansion of operations is an important reason why a firm chooses to borrow from a foreign bank. Thus, the benefits of expanding operations and flexibility in negotiation established through foreign-bank relationships might outweigh the cost of paying higher terms.

Firms can also diversify their sources of funding across countries through established relationships with foreign banks. Diversification in capital sources can help firms hedge against future disruptions in a particular capital market. If there is a credit supply shock in their home country, foreign bank borrowers are more able than domestic bank borrowers to shift to alternative funding channels in other countries that are less affected. The recent 2008–2009 financial crisis provides a useful setting to test this prediction. Several studies have documented that during the financial crisis, banks sharply cut their lending and increased loan interest rates to corporate sectors (see, e.g., Ivashina and Scharfstein, 2010; Santos, 2010). If lenders in other countries were less affected by the supply shock, the difference in loan supply between foreign and domestic banks would increase, especially during the financial crisis. Indeed, Figure A1 shows an increase in the share of foreign banks in total lending during the financial crisis. Besides, the results in Appendix Table A6 show that foreign banks do not charge higher interest rates during the crisis period when domestic banks are typically financially constrained. Furthermore, the results in Appendix Table A7 indicate that foreign banks do not charge higher loan terms when the credit market conditions are tightening. These findings suggest that firms are not credit constrained and thereby forced to borrow from foreign banks with higher costs due to domestic credit supply contractions.

### 2.5.2 Ex-post borrower performance

It is important to understand whether borrowing from a foreign bank generates economic consequences for a firm. The evidence so far shows that compared to domestic bank borrowers, foreign bank borrowers are larger and rated firms. At the same time, foreign lenders are significantly less likely to include financial covenants in their credit agreements, which indicated that they do not monitor borrowers to the same extent as domestic banks do. This raises a question as to whether foreign bank borrowers perform differently than domestic bank borrowers. To address this question, this section explores the ex-post performance of borrowers as well as the ex-ante announcement returns around loan originations.

#### 2.5.2.1 Future performance of foreign bank borrowers

I start by asking whether foreign bank borrowers are performing differently than domestic bank borrowers. To do so, I track borrowers' profitability, investment, sales, and credit rating. These analyses shed light on the effects of foreign loans on borrower policies and growth. Panel B of Table 2.8 reports the results. Estimates suggest that foreign bank loans are significantly associated with an increase in profitability and sales growth, suggesting that cross-border borrowing affect the policies and growth of firms. Overall, these results indicate that conditional on firm characteristics, foreign bank borrowers perform better than domestic bank borrowers following loan origination.

#### 2.5.2.2 Announcement returns around loan origination

Several studies analyses how borrower's stock price reaction around bank loan announcements. For instance, James (1987) shows that borrowers experience a positive and significant stock price reaction that equals on average 2% over a two-day period surrounding the announcement. Indeed, banks might play a special role as providers of informative signals about the quality and value of their borrowers (James, 1987). Such signals, however, may have a quality of their own as the banks' selection and monitoring abilities may differ (Billett et al., 1995). My previous results support the argument that domestic banks have an informational advantage in screening and monitoring local borrowers. If local banks are more informed than foreign banks due to their physical proximity, for example, the abnormal returns following the loan announcements should be larger than those observed for foreign bank loans.

In Table 2.9, I analyze announcement returns around loan origination for foreign versus domestic bank borrowers. In Panel A, I calculate cumulative abnormal returns on the announcement date. Abnormal returns are calculated based on the market model estimated using daily returns over the year ending 20 calendar days prior to loan origination. I require at least 100 daily return observations to estimate market beta. The results show that when firms announce a loan from a domestic bank, the stock price reaction for all six event windows considered is positive and statistically significant at the 1% level. While foreign bank borrowers display positive cumulative abnormal returns, they do not appear to be significant for any event window. In Panel B, I explore the effects of lender type on borrower's stock price in a multivariate framework by considering borrower and loan characteristics. The dependent variable is the 3-day cumulative abnormal return over the (–1, +1) window. The coefficient of foreign lead arranger dummy variable is negative and significant in some specifications but not when I include firm fixed effects. It indicates that foreign bank loans experience announcement returns that are 0.2% lower than those of domestic bank loans. This evidence suggests that investors value relationships with banks that have easier access to private information about the firms.

## 2.6 Why do foreign banks charge higher rates?

After having established that foreign banks are associated with higher loan spreads, I investigate what drives these results.

### 2.6.1 The role of physical and cultural distance

Since the distance between arrangers and borrowers increases monitoring cost and moral hazard, I expect that distant arrangers need to show more skin in the game to credibly commit to proper due diligence and need to form more expensive loan pricing (Giannetti and Yafeh, 2012). My fourth hypothesis states that loan spreads increase with the physical and cultural distance between foreign lenders and borrowers due to asymmetric information.

I use the circle distance between the capital cities of borrowers and foreign bank countries as a proxy for asymmetric information.[25] I measure cultural distance following Inglehart and Welzel (2005). They analyze the World Values Surveys (WVS), which were designed to measure all major categories of human concern, from religion to politics to economic and

[25] With the longitude and latitude data for both the lender and the borrower, one can calculate the spherical distance between the two. See Coval and Moskowitz (2001) and Dass and Massa (2011) for details of the estimating formula. I use the same methodology.

social life and find that two dimensions dominate: (1) Traditional vs. Secular-rational values and (2) Survival vs. Self-expression values. These two dimensions explain more than 70 percent of the cross-cultural variance across the individual WVS categories. Their cultural distance measure is a combination of both dimensions. For my own proxy, I calculate the Euclidean distance of these values between the arranger's country and the U.S. as in Giannetti and Yafeh (2012).[26]

The results are provided in Table 2.10. Consistent with the informational asymmetries and costly monitoring channel, I find that the coefficients for physical and cultural distance are positive and significant at the 1% level.[27] The findings suggest that compared to local banks, foreign lenders find it harder to collect local information on the borrower, establish long-term relations, monitor the way funds are being used, and finally enforce contractual terms. Consequently, this evidence implies that the ability of lenders to manage information problems varies with the location of the borrower, which in turn implies that nationality differences per se are particularly important to loan pricing.

### 2.6.2 The role of lending relationships

Information asymmetry between lenders and borrowers is at the core of financial intermediation. Lenders invest in costly information production to assess the creditworthiness of potential borrowers, thereby reducing inefficiencies that arise from adverse selection. After loan contracting, lenders monitor borrowers to alleviate agency conflicts between managers and shareholders. Bank monitoring yields borrower-specific information that is durable, reusable (Boot and Thakor, 2000), and valuable if borrowers and lenders engage in repeated interactions (Bharath et al., 2009). Relationship borrowers may even be locked in due to the information asymmetries between outside lenders and the relationship lender (Rajan, 1992).

[26] I also find that my results are robust to the use of alternative measures of cultural distance constructed by Hofstede (2001). In particular, Hofstede's "power-distance" score captures the centralization of decision power and allows us to measure cultural differences related to organizational structure. Results are available upon request from the author.

[27] In columns (3) and (6) the coefficients of physical and cultural distance are not statistically significant due to the high correlation between these two variables.

If lending to a new borrower is invaluable to a lender, then the lender might ask extra pricing terms. I thus define the variable New Relation as a dummy variable equal to one if the lead bank lends to the borrower for the first time, and zero otherwise. It quantifies whether the effect of foreign arrangers on loan pricing is stronger for new bank relationships. In Table 2.11, I find that the coefficient of the interaction term is negative but insignificant for loan spreads, and positive but insignificant for the total cost of borrowing. The insignificant interaction term implies that foreign lenders do not offer a reduction or benefit in the overall for the first time.

I also examine how lending relationships with a bank evolve over time. I construct the relationship lending variables in the spirit of Bharath et al. (2009) who find that repeated borrowing from the same lender translates into lower spreads.[28] The measures of relationship lending include a dummy variable equal to one if a borrower and a lender interacted in the last five years before a deal (Old Relation (Dummy)), the share of the number of loans between a borrower and a lender as a fraction of the total number of loans of a borrower in the last five years before a deal (Old Relation (Number)), and the share of the loan amount between a borrower and a lender as a fraction of the total loan amount of a borrower in the last five years before a deal (Old Relation (Amount)). I find no evidence that foreign bank borrowers pay lower loan spreads or total cost of borrowing in repeated interactions. The results show that, on average, the clients of foreign banks are firms with 'weaker' bank-lending relationships.

Taken together, these results indicate that foreign lenders are less likely to participate in relationship lending and that they do not offer different terms for repeated interactions with a given borrower. While domestic banks base their pricing on the length, depth, and breadth of their relationship with the borrower, foreign banks have a more transaction-based pricing approach. These findings suggest that domestic banks rely more on soft information

[28]By employing Dealscan data, Bharath et al. (2009) show that borrowers with an existing bank relationship pay 10 to 17 basis points less on their loans, and have fewer collateral requirements. They attribute these effects to reduced asymmetric information due to the private information obtained from the borrower's existing relationship.

acquired through relationships with clients.

## 2.7 Further Analyses

In this section, I first study whether foreign funding is cheaper for multinational firms. Second, I investigate the role of participant banks. Third, I do some subsample analyses based on the origin (Canadian vs. European) and the type (commercial vs. investment) of foreign banks. Finally, I explore whether the U.S. branches of foreign banks charge higher terms when they lend to U.S. firms and if U.S. banks charge higher rates when they lend to foreign firms.

### 2.7.1 Foreign banks and multinational firms

A recent paper by Jang (2017) documents that U.S. multinationals are more likely to borrow from foreign banks and the corresponding loans have better pricing terms. Indeed, one of the benefits of international corporate diversification is that expanding operations overseas can improve access to capital markets and lower the cost of capital. One feature of multinational firms is that collecting private information on those firms might be relatively easier compared to purely domestic firms. A firm is defined as a multinational if any of its foreign pretax income (Compustat item: PIFO) or foreign income tax (Compustat item: TXFO) is not missing in at least one year over the previous three years. In line with the argument that collecting soft information on multinational firms is relatively easier, the results in Appendix Table A8 show that foreign banks charge lower loan spreads for multinational borrowers consistent with the findings in Jang (2017).

### 2.7.2 Participant banks

I also examine the role of participant banks on loan pricing. To do so, I construct a variable, *Participants*, the number of foreign participants over the total number of participants in a syndicate. This measure attracts a negative and significant coefficient as shown in Appendix Table A9, suggesting that an increase in foreign participation is associated with lower spreads but higher fees. Notably, the magnitude of foreign arranger dummy increases when I include foreign participants. The coefficient on the interaction term between *Foreign* and *Participants* is negative but statistically insignificant, indicating that higher loan spreads by foreign banks do not significantly change with the participant banks type (foreign vs. domestic).

### 2.7.3 Canadian vs. European banks

Since in the data around 30% of foreign loans are from Canada and around 60% are from European countries, I investigate whether banks from these countries offer different loan terms compared to domestic banks in a subsample analysis. The results in Appendix Table A10 show that European banks are more likely to charge higher rates. These findings are consistent with the asymmetric information problems and costly monitoring that arise across borders and exacerbated by distance.

### 2.7.4 Commercial vs. Investment Banks

To identify commercial bank lenders, I start from lenders whose type in Dealscan is *US Bank, African Bank, Asian-Pacific Bank, Foreign Bank, Eastern Europe/Russian Bank, Middle Eastern Bank, Western European Bank,* or *Thrift/S&L*. I manually exclude the observations that are classified as a bank by Dealscan but actually are not, such as the General Motors Acceptance Corporation (GMAC) Commercial Finance. I went through all the syndicated loans manually, one-by-one. The results in Appendix Table A11 show that investment banks charge higher rates compared to commercial banks. However, loans arranged by foreign investment banks carry lower spreads.

### 2.7.5 Loans initiated by the U.S. branches of foreign banks

I also look at whether U.S. branches of foreign banks charge higher loan terms when they lend to U.S firms. There are a total of 230 loans extended by the U.S. branches of foreign banks to 117 U.S. firms. The results in Appendix Table A12 show that the U.S. branches of foreign banks do not charge different loan spreads compared to domestic banks.

### 2.7.6 U.S. Banks as Foreign Lenders

I also investigate if U.S. banks charge higher rates when they lend to foreign firms. There are a total of 532 loans extended by U.S. banks to 205 foreign firms. Among these loans, 223 of them are borrowed by European firms (81 firms). The results in Appendix Table A13 show that U.S. banks also charge higher rates compared to domestic banks when lending abroad. When I look at loans extended by U.S. banks to European firms, I do not find empirical evidence that U.S. banks charge higher rates.

## 2.8 Conclusion

Cross-border loan supply has become an increasingly important source of funding. In this paper, I examine U.S. firms' motives for participating in cross-border syndicated loans with foreign banks. I find that foreign lead arrangers charge on average around 16 bps higher spread on their syndicated loans compared to local arrangers. A potential reason for this finding might be that foreign banks cater to different, and especially riskier clients than their domestic counterparts. Using various matching sample techniques and exploiting within-firm variation, I show that the borrowing spread continues to hold, thereby alleviating endogeneity concerns.

I provide novel evidence on the underlying forces that drive borrowing from foreign lead arrangers. Firms borrowing from foreign banks experience a significant increase in their foreign income after loan origination compared to firms borrowing from local banks. In addition, foreign bank borrowers are more likely to become multinational and participate in cross-border M&As in the lender's region after borrowing from foreign banks. These results suggest that international expansion of businesses is an important reason why a firm borrows from a foreign lender.

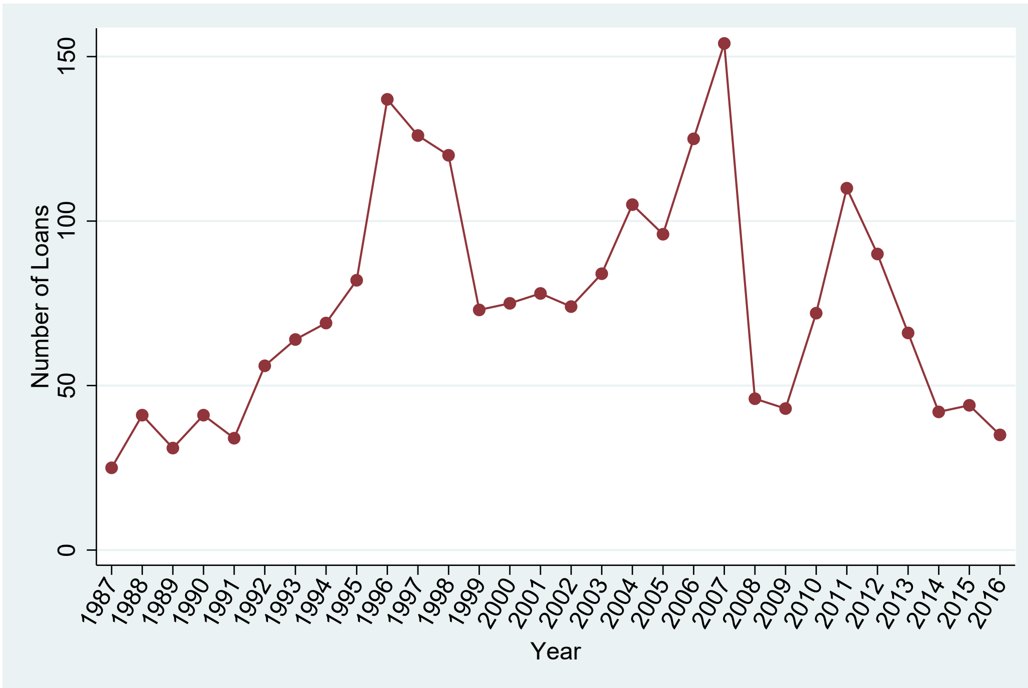
Loan spreads furthermore increase with the physical and cultural distance between borrowers and foreign lenders. In addition, foreign banks are less likely to participate in relationship lending with a given borrower. Foreign lenders are also significantly less likely than domestic banks to include financial covenants in their loans, suggesting that foreign lenders rely less on financial covenants to monitor borrowers' ex-post performance. These findings are consistent with an informational asymmetry and costly monitoring channel that arise across borders and exacerbated by distance.

The findings have potential implications for borrowers, lenders, and policy makers. While borrowing from foreign banks is more costly, the established relationships allow firms to expand their operations overseas, establish a reputation in international markets, and diversify their funding sources. Although foreign banks lack private information, one potential motivation for cross-border lending is to benefit from higher profits by charging higher loan spreads. Besides, foreign banks can use the syndicated loan market to establish a market presence and expand their activity abroad. For policy makers, the level of bank competition and its impact on customers has been raised on numerous occasions. The results in this paper lend support to the argument that while markets have become more globalized due to technological innovations, information costs continue to exist across borders. My findings suggest that the role of foreign banks in global financial integration remains important. Domestic banks that are close to local borrowers may continue to have a comparative advantage in screening and monitoring. Their ability to do so may, however, usefully be leveraged by co-lending with international banks.

**Figure 2.1: Number of loans by foreign and domestic banks over years**

This figure presents the total number of cross-border and domestic loans extended to the U.S. borrowers over the period 1987-2016.

Number of loans by foreign lead arrangers




Number of loans by domestic lead arrangers

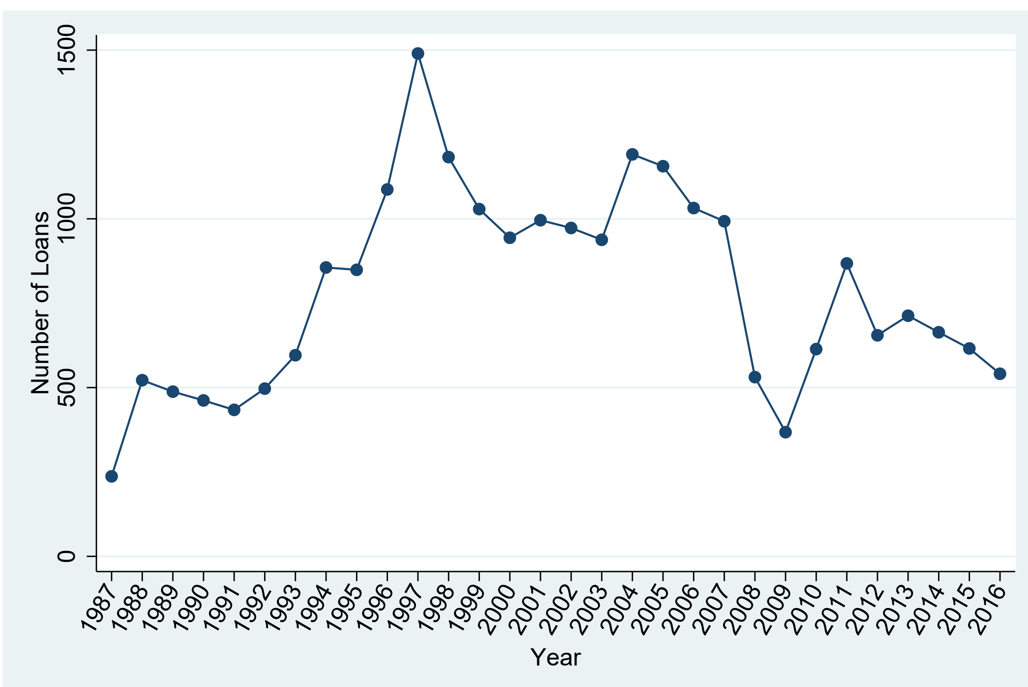
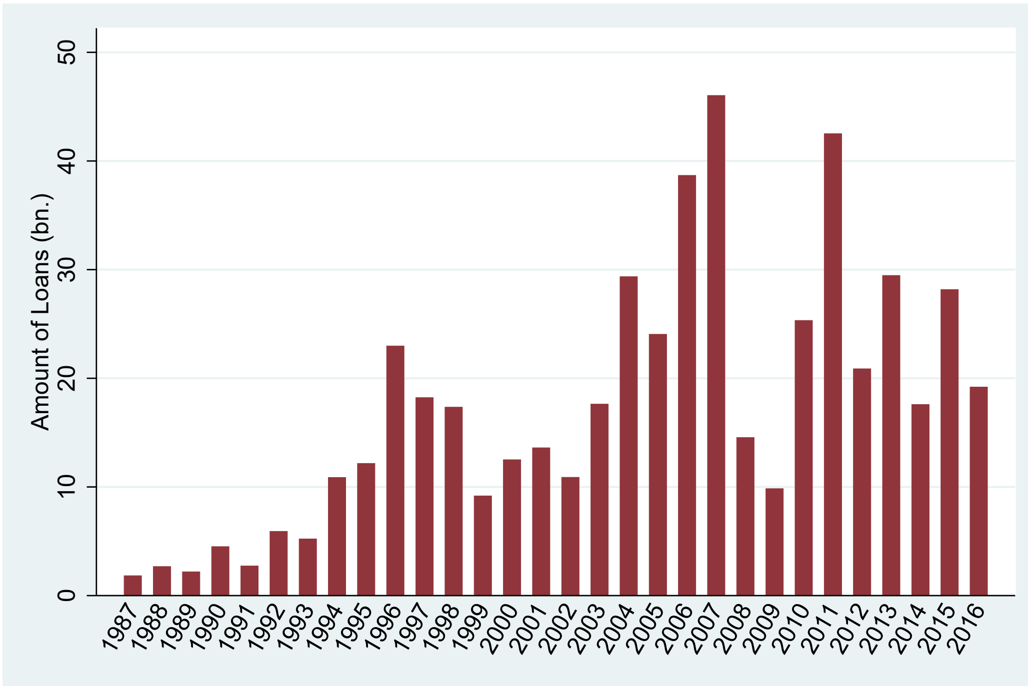


**Figure 2.2: Amount of loans by foreign and domestic banks over years**

This figure presents the total value of cross-border and domestic loans extended to the U.S. borrowers over the period 1987-2016.

Amount of loans (bn.) by foreign lead arrangers




Amount of loans (bn.) by domestic lead arrangers

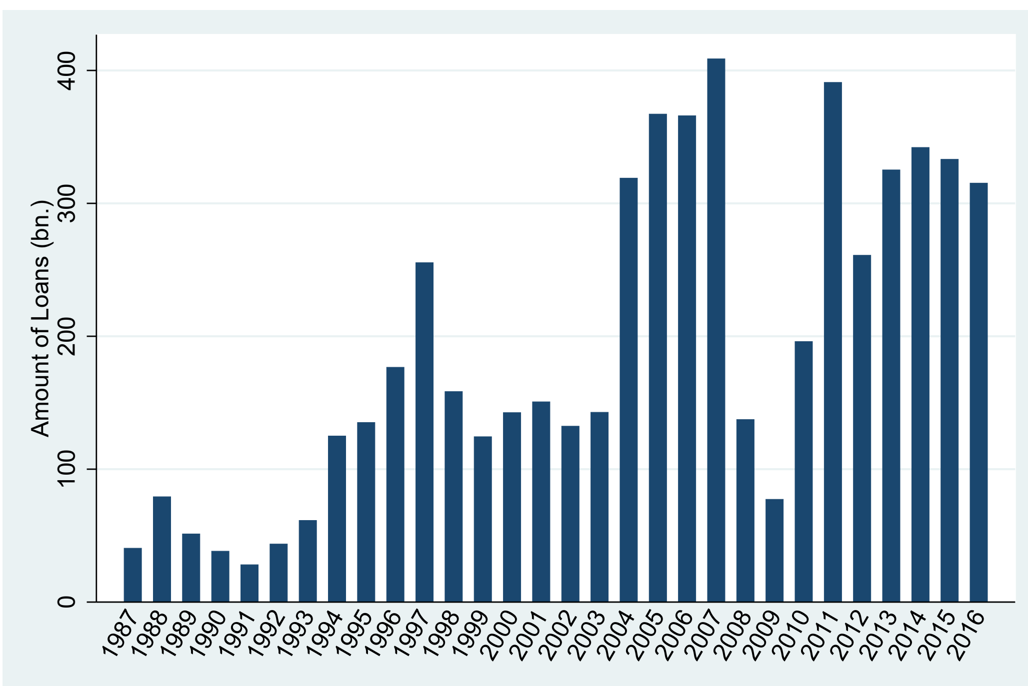
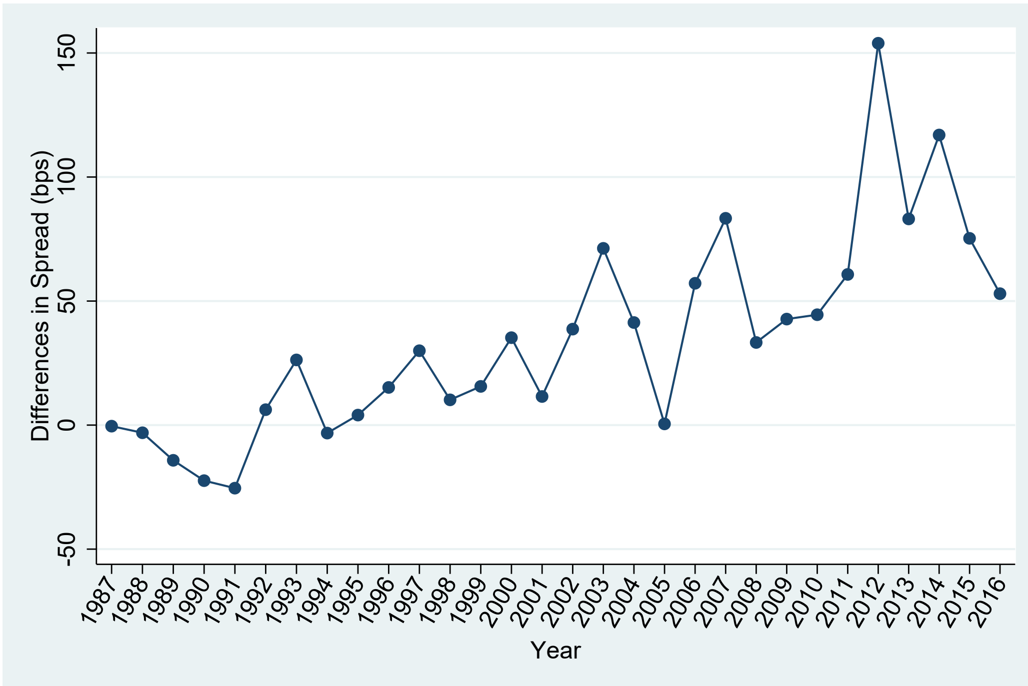


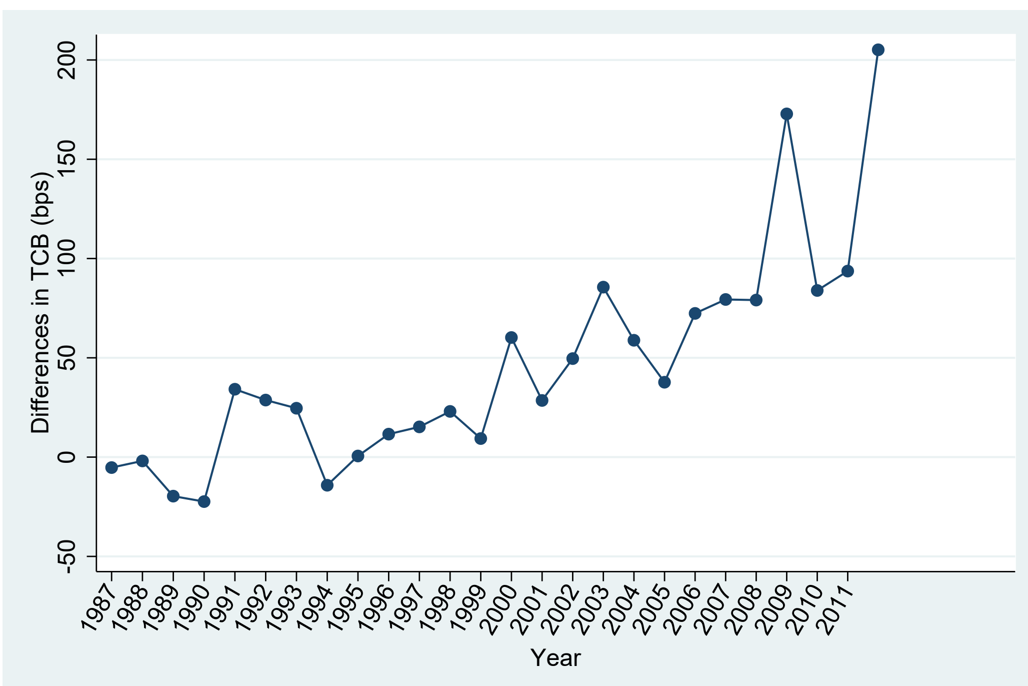
**Figure 2.3: Difference in loan spreads and total cost of borrowing (TCB)**

This figure presents the difference in loan spreads and total cost of borrowing (TCB) between foreign and domestic banks over the period 1987-2016.

Difference in loan spreads (bps)




Difference in TCB (bps)



## Table 2.1: Summary statistics for foreign vs. domestic bank loans

This table reports firm and loan characteristics for foreign-bank versus domestic-bank loans. The overall sample covers 25,111 USD-denominated loans (2,115 foreign-led and 22,996 domestic-led) originated by 1,062 banks (184 foreign and 878 domestic) to 5,383 publicly traded, non-financial, and non-utility U.S. borrowers between 1987 and 2016. Among these firms, 196 (4,555) of them only borrow from foreign (domestic) banks whereas 632 of them borrow from both types of lenders. For each variable, the number of observations ($N$), mean, median, and standard deviation (SD) are reported. Loan and borrower characteristics are collected from Dealscan, Compustat and CRSP, respectively. Statistical significance for differences in means is assessed using $t$-tests that allow for unequal variances across groups. I define all variables in Appendix C. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Foreign Bank Loans (1) | | | | Domestic Bank Loans (2) | | | | Difference (2)-(1) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $N$ | Mean | Median | SD | $N$ | Mean | Median | SD | Diff. | ($t$-stat) |
| **Loan Characteristics** | | | | | | | | | | |
| Spread [bps] | 2,115 | 232.48 | 225.00 | 140.10 | 22,996 | 191.60 | 175.00 | 122.42 | -40.88*** | (-12.97) |
| Total Cost of Borrowing [bps] | 1,231 | 188.23 | 150.36 | 139.82 | 13,324 | 144.77 | 111.78 | 120.79 | -43.46*** | (-10.55) |
| Upfront Fee [bps] | 624 | 71.79 | 50.00 | 72.61 | 5,548 | 63.75 | 50.00 | 62.28 | -8.04** | (-2.66) |
| Commitment Fee [bps] | 858 | 42.27 | 50.00 | 17.67 | 10,910 | 35.61 | 37.50 | 16.56 | -6.66*** | (-10.67) |
| Facility Fee [bps] | 175 | 20.56 | 15.00 | 16.57 | 3,783 | 21.43 | 15.00 | 18.23 | 0.87 | (0.68) |
| Amount [USD mn.] | 2,115 | 234.92 | 100.00 | 366.43 | 22,996 | 251.52 | 100.00 | 426.49 | 16.60* | (1.96) |
| Maturity [months] | 2,115 | 57.00 | 60.00 | 20.29 | 22,996 | 50.26 | 60.00 | 19.41 | -6.74*** | (-14.67) |
| Facility Number | 2,115 | 2.05 | 2.00 | 1.21 | 22,996 | 1.80 | 2.00 | 1.09 | -0.25*** | (-9.04) |
| Secured [0/1] | 2,115 | 0.91 | 1.00 | 0.28 | 22,996 | 0.85 | 1.00 | 0.36 | -0.06*** | (-9.70) |
| Financial Covenants [0/1] | 2,115 | 0.49 | 0.00 | 0.50 | 22,996 | 0.56 | 1.00 | 0.50 | 0.08*** | (6.91) |
| Prime Base Rate [0/1] | 2,115 | 0.57 | 1.00 | 0.50 | 22,996 | 0.70 | 1.00 | 0.46 | 0.14*** | (12.08) |
| Performance Pricing [0/1] | 2,115 | 0.33 | 0.00 | 0.47 | 22,996 | 0.42 | 0.00 | 0.49 | 0.09*** | (8.19) |
| Credit Line [0/1] | 2,115 | 0.54 | 1.00 | 0.50 | 22,996 | 0.70 | 1.00 | 0.46 | 0.16*** | (14.20) |
| Term Loan [0/1] | 2,115 | 0.46 | 0.00 | 0.50 | 22,996 | 0.30 | 0.00 | 0.46 | -0.16*** | (-14.20) |
| Number of Lenders | 2,115 | 6.79 | 4.00 | 9.94 | 22,996 | 6.57 | 4.00 | 7.47 | -0.22 | (-1.00) |
| Lead Share [0-1] | 570 | 0.50 | 0.33 | 0.38 | 8,315 | 0.51 | 0.40 | 0.37 | 0.01 | (0.90) |
| Foreign Participants [0-1] | 1,583 | 0.32 | 0.31 | 0.29 | 16,625 | 0.24 | 0.20 | 0.25 | -0.09*** | (-11.21) |
| New Relation [0/1] | 2,115 | 0.65 | 1.00 | 0.48 | 22,996 | 0.60 | 1.00 | 0.49 | -0.05*** | (-4.75) |
| Old Relation (Dummy) [0/1] | 2,115 | 0.33 | 0.00 | 0.47 | 22,996 | 0.38 | 0.00 | 0.48 | 0.05*** | (4.42) |
| Old Relation (Number) [0-1] | 1,532 | 0.31 | 0.00 | 0.40 | 16,772 | 0.39 | 0.19 | 0.43 | 0.08*** | (7.39) |
| Old Relation (Amount) [0-1] | 1,532 | 0.32 | 0.00 | 0.41 | 16,772 | 0.40 | 0.11 | 0.44 | 0.08*** | (7.32) |
| **Borrower Characteristics** | | | | | | | | | | |
| Total Assets [USD bn.] | 2,115 | 2.54 | 0.75 | 5.74 | 22,996 | 2.52 | 0.50 | 6.26 | -0.02 | (-0.12) |
| Leverage [number] | 2,115 | 0.35 | 0.33 | 0.24 | 22,996 | 0.30 | 0.27 | 0.22 | -0.05*** | (-9.39) |
| Profitability [number] | 2,115 | 0.12 | 0.12 | 0.10 | 22,996 | 0.12 | 0.13 | 0.10 | -0.00 | (-0.66) |
| Tangibility [number] | 2,115 | 0.35 | 0.30 | 0.26 | 22,996 | 0.30 | 0.24 | 0.22 | -0.05*** | (-8.27) |
| Current Ratio [number] | 2,115 | 1.87 | 1.49 | 1.32 | 22,996 | 2.03 | 1.72 | 1.29 | 0.17*** | (5.52) |
| Market-to-Book [number] | 2,115 | 1.73 | 1.44 | 0.96 | 22,996 | 1.72 | 1.43 | 0.96 | -0.00 | (-0.14) |
| Return Volatility | 2,115 | 0.03 | 0.03 | 0.02 | 22,996 | 0.03 | 0.03 | 0.03 | 0.00*** | (4.81) |
| Investment Grade [0/1] | 1,140 | 0.12 | 0.00 | 0.32 | 9,352 | 0.20 | 0.00 | 0.40 | 0.08*** | (7.69) |
| Not Rated [0/1] | 2,115 | 0.46 | 0.00 | 0.50 | 22,996 | 0.59 | 1.00 | 0.49 | 0.13*** | (11.69) |
| Multinational [0/1] | 2,115 | 0.49 | 0.00 | 0.50 | 22,996 | 0.48 | 0.00 | 0.50 | -0.01 | (-0.78) |

## Table 2.2: Probability of borrowing from a foreign lender

This table reports the results from linear probability models of whether a loan is extended by a foreign lender. The dependent variable, *foreign*, is a dummy indicating whether a loan is extended by a foreign lead arranger or not (=1 if use of foreign lead, =0 otherwise). The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. See Appendix C for variable definitions. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Foreign | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Total Assets)$_{t-1}$ | 0.010*** | 0.014** | | | 0.012*** | 0.020*** |
| | (3.30) | (2.26) | | | (3.09) | (3.20) |
| Leverage$_{t-1}$ | 0.035* | 0.019 | | | 0.018 | 0.021 |
| | (1.94) | (0.85) | | | (1.02) | (0.92) |
| Profitability$_{t-1}$ | -0.033 | 0.032 | | | -0.031 | 0.033 |
| | (-1.07) | (0.73) | | | (-1.00) | (0.76) |
| Tangibility$_{t-1}$ | 0.026 | -0.050 | | | 0.026 | -0.048 |
| | (1.23) | (-1.26) | | | (1.29) | (-1.21) |
| Current Ratio$_{t-1}$ | -0.001 | -0.003 | | | -0.002 | -0.003 |
| | (-0.44) | (-0.93) | | | (-0.67) | (-1.02) |
| Market-to-Book$_{t-1}$ | 0.008** | 0.000 | | | 0.008*** | 0.001 |
| | (2.23) | (0.07) | | | (2.63) | (0.32) |
| Not Rated$_{t-1}$ | -0.043*** | -0.014 | | | -0.032** | -0.011 |
| | (-2.84) | (-1.29) | | | (-2.21) | (-1.01) |
| Return Volatility$_{t-1}$ | -0.205* | -0.065 | | | -0.183 | -0.079 |
| | (-1.68) | (-0.47) | | | (-1.51) | (-0.57) |
| Multinational$_{t-1}$ | 0.002 | -0.011 | 0.007 | -0.003 | 0.004 | -0.010 |
| | (0.25) | (-1.09) | (1.01) | (-0.34) | (0.55) | (-0.99) |
| Log(Amount)$_t$ | | | 0.005*** | -0.004 | -0.003 | -0.008*** |
| | | | (2.59) | (-1.55) | (-1.08) | (-2.97) |
| Log(Maturity)$_t$ | | | 0.027*** | 0.020*** | 0.025*** | 0.019*** |
| | | | (4.61) | (3.40) | (4.25) | (3.21) |
| Secured$_t$ | | | 0.013** | 0.009 | 0.015** | 0.009 |
| | | | (2.13) | (1.34) | (2.30) | (1.37) |
| Financial Covenants$_t$ | | | -0.018** | -0.015* | -0.015* | -0.013* |
| | | | (-2.33) | (-1.87) | (-1.96) | (-1.65) |
| Performance Pricing$_t$ | | | -0.024*** | -0.019*** | -0.023*** | -0.019*** |
| Rating FE | Yes | No | Yes | No | Yes | No |
| Industry FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | No | No | Yes | Yes | Yes | Yes |
| Loan Purpose FE | No | No | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes | No | Yes |
| Observations | 25111 | 23774 | 25111 | 23774 | 25111 | 23774 |
| Adjusted $R^2$ | 0.025 | 0.386 | 0.039 | 0.391 | 0.043 | 0.393 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm |

### Table 2.3: The effect of foreign banks on loan pricing

This table presents results for linear regressions of all-in-drawn loan spread (Spread) and of total cost of borrowing (TCB) on the foreign lead arranger dummy, loan features, and borrower characteristics. The dependent variable is the logarithm of Spread or TCB. The key explanatory variable is *foreign*, which is a dummy variable that equals one if the lender is a foreign bank, and zero otherwise. Columns (1) and (5) shows results for the main regression model with rating, industry (two-digit SIC code), year, loan type and loan purpose fixed effects. In columns (2) and (6), I replace industry and year fixed effects by industry-year fixed effects. Columns (3) and (7) shows the results for firm fixed effects instead of rating and industry fixed effects. In columns (4) and (8), I use loan type, loan purpose, and firm-year fixed effects. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, Compustat, and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\text{Foreign}_k$ | 0.081*** | 0.083*** | 0.065*** | 0.081* | 0.061*** | 0.063*** | 0.037** | 0.117*** |
| | (4.48) | (4.71) | (2.85) | (1.80) | (3.55) | (3.71) | (2.11) | (2.59) |
| $\text{Log(Amount)}_t$ | -0.054*** | -0.056*** | -0.086*** | -0.055*** | -0.020*** | -0.021*** | -0.035*** | -0.030*** |
| | (-6.55) | (-6.97) | (-11.15) | (-9.11) | (-3.10) | (-3.44) | (-4.51) | (-5.37) |
| $\text{Log(Maturity)}_t$ | 0.009 | 0.008 | 0.012 | 0.036** | -0.166*** | -0.166*** | -0.174*** | -0.127*** |
| | (0.74) | (0.68) | (0.92) | (2.32) | (-13.59) | (-13.57) | (-10.83) | (-9.00) |
| $\text{Number of Lenders}_t$ | -0.007*** | -0.007*** | -0.006*** | -0.005*** | -0.001 | -0.001 | -0.002* | -0.002** |
| | (-6.33) | (-6.30) | (-4.37) | (-2.81) | (-1.22) | (-1.55) | (-1.86) | (-2.12) |
| $\text{Secured}_t$ | 0.375*** | 0.370*** | 0.281*** | 0.358*** | 0.359*** | 0.354*** | 0.290*** | 0.150*** |
| | (25.85) | (25.58) | (17.12) | (6.68) | (28.21) | (28.25) | (15.29) | (3.02) |
| $\text{Financial Covenants}_t$ | 0.041*** | 0.043*** | 0.041*** | -0.020 | 0.035** | 0.036** | 0.052*** | 0.025 |
| | (2.86) | (3.05) | (2.67) | (-0.58) | (2.43) | (2.50) | (2.79) | (0.67) |
| $\text{Prime Base Rate}_t$ | -0.020 | -0.021 | 0.013 | -0.035 | 0.117*** | 0.114*** | 0.093*** | 0.034 |
| | (-1.29) | (-1.41) | (0.83) | (-1.27) | (7.79) | (7.66) | (4.91) | (1.10) |
| $\text{Performance Pricing}_t$ | -0.026* | -0.027* | -0.045*** | -0.104*** | -0.122*** | -0.121*** | -0.120*** | -0.142*** |
| | (-1.94) | (-1.95) | (-3.27) | (-5.79) | (-10.02) | (-9.92) | (-7.82) | (-8.67) |
| $\text{Log(Total Assets)}_{t-1}$ | -0.010 | -0.009 | -0.051*** | 0.166** | -0.080*** | -0.080*** | -0.107*** | 0.082 |
| | (-1.15) | (-1.07) | (-3.89) | (2.12) | (-10.07) | (-10.32) | (-8.28) | (1.05) |
| $\text{Leverage}_{t-1}$ | 0.445*** | 0.449*** | 0.406*** | 0.219 | 0.584*** | 0.584*** | 0.499*** | 0.160 |
| | (16.16) | (16.58) | (10.69) | (0.97) | (21.30) | (21.13) | (9.48) | (0.88) |
| $\text{Profitability}_{t-1}$ | -0.439*** | -0.437*** | -0.669*** | -0.191 | -0.890*** | -0.905*** | -0.902*** | -1.018* |
| | (-7.41) | (-7.29) | (-8.16) | (-0.44) | (-13.10) | (-13.31) | (-9.66) | (-1.68) |
| $\text{Tangibility}_{t-1}$ | -0.053* | -0.056* | -0.164** | -0.267 | 0.054** | 0.048* | -0.071 | -0.535 |
| | (-1.81) | (-1.93) | (-2.16) | (-0.42) | (2.03) | (1.82) | (-0.81) | (-0.78) |
| $\text{Current Ratio}_{t-1}$ | -0.003 | -0.003 | 0.007 | -0.047 | -0.015*** | -0.015*** | -0.013* | -0.169*** |
| | (-0.64) | (-0.77) | (1.15) | (-1.25) | (-3.31) | (-3.45) | (-1.79) | (-2.73) |
| $\text{Market-to-Book}_{t-1}$ | -0.052*** | -0.054*** | -0.061*** | -0.032 | -0.058*** | -0.058*** | -0.074*** | -0.067 |
| | (-8.31) | (-8.33) | (-6.46) | (-0.57) | (-8.31) | (-8.10) | (-10.37) | (-1.05) |
| $\text{Return Volatility}_{t-1}$ | 1.729*** | 1.679*** | 1.571*** | -0.182 | 3.025*** | 3.054*** | 2.523*** | -0.827 |
| | (6.60) | (6.34) | (5.84) | (-0.26) | (13.33) | (13.43) | (7.78) | (-0.95) |
| Rating FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Industry FE | Yes | No | No | No | Yes | No | No | No |
| Year FE | Yes | No | No | No | Yes | No | No | No |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | No | Yes | Yes | No | No | Yes | Yes | No |
| Borrower FE | No | No | Yes | No | No | No | Yes | No |
| Borrower x Year FE | No | No | No | Yes | No | No | No | Yes |
| Observations | 25111 | 25104 | 23765 | 13574 | 14555 | 14540 | 13609 | 7124 |
| Adjusted $R^2$ | 0.504 | 0.508 | 0.657 | 0.810 | 0.788 | 0.789 | 0.848 | 0.909 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

## Table 2.4: Non-price terms of foreign versus domestic bank loans

This table reports the results from linear regressions of non-price loan terms on lender type indicators, loan and firm characteristics. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Collateral | | Financial Covenant | | Log(Maturity) | | Amount | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\text{Foreign}_k$ | $0.024^{***}$ | $0.020^{*}$ | $-0.047^{***}$ | $-0.054^{***}$ | $0.055^{***}$ | $0.049^{***}$ | -0.026 | $-0.108^{***}$ |
| | (2.87) | (1.72) | (-3.06) | (-2.78) | (4.26) | (3.09) | (-0.80) | (-2.80) |
| $\text{Log(Amount)}_t$ | $-0.026^{***}$ | $-0.026^{***}$ | $0.024^{***}$ | $0.030^{***}$ | $0.080^{***}$ | $0.064^{***}$ | | |
| | (-10.12) | (-8.55) | (4.99) | (6.34) | (19.14) | (14.20) | | |
| $\text{Log(Maturity)}_t$ | $0.014^{***}$ | $0.014^{**}$ | -0.008 | -0.006 | | | $0.404^{***}$ | $0.336^{***}$ |
| | (2.75) | (2.16) | (-1.01) | (-0.66) | | | (19.56) | (14.42) |
| $\text{Number of Lenders}_t$ | $-0.001^{**}$ | $-0.002^{***}$ | $0.010^{***}$ | $0.010^{***}$ | $0.003^{***}$ | $0.002^{***}$ | $0.042^{***}$ | $0.036^{***}$ |
| | (-2.55) | (-3.07) | (11.01) | (9.47) | (4.32) | (3.55) | (11.55) | (8.92) |
| $\text{Financial Covenants}_t$ | $-0.157^{***}$ | $-0.161^{***}$ | | | -0.008 | -0.006 | $0.124^{***}$ | $0.163^{***}$ |
| | (-22.28) | (-18.69) | | | (-1.01) | (-0.66) | (4.82) | (6.19) |
| $\text{Secured}_t$ | | | $-0.252^{***}$ | $-0.245^{***}$ | $0.024^{***}$ | $0.022^{**}$ | $-0.225^{***}$ | $-0.213^{***}$ |
| | | | (-25.69) | (-20.90) | (2.75) | (2.16) | (-9.30) | (-8.03) |
| $\text{Log(Total Assets)}_{t-1}$ | $-0.016^{***}$ | $-0.017^{***}$ | $-0.059^{***}$ | $-0.050^{***}$ | $-0.010^{**}$ | 0.007 | $-0.420^{***}$ | $-0.510^{***}$ |
| | (-4.86) | (-2.62) | (-11.12) | (-5.54) | (-2.21) | (0.82) | (-32.37) | (-25.41) |
| $\text{Leverage}_{t-1}$ | $0.120^{***}$ | $0.083^{***}$ | $-0.047^{**}$ | $-0.066^{**}$ | $0.070^{***}$ | $-0.099^{***}$ | $0.222^{***}$ | -0.015 |
| | (9.80) | (4.06) | (-2.28) | (-2.25) | (2.91) | (-3.23) | (4.59) | (-0.26) |
| $\text{Profitability}_{t-1}$ | $-0.172^{***}$ | $-0.176^{***}$ | $0.289^{***}$ | $0.115^{*}$ | $0.479^{***}$ | $0.353^{***}$ | $0.731^{***}$ | $0.542^{***}$ |
| | (-7.21) | (-4.51) | (7.28) | (1.81) | (11.33) | (5.30) | (7.98) | (4.43) |
| $\text{Tangibility}_{t-1}$ | -0.014 | -0.052 | 0.015 | 0.058 | 0.028 | 0.025 | 0.083 | $0.200^{**}$ |
| | (-0.89) | (-1.27) | (0.76) | (1.05) | (1.36) | (0.48) | (1.61) | (1.98) |
| $\text{Current Ratio}_{t-1}$ | $-0.004^{*}$ | $-0.008^{**}$ | 0.002 | -0.005 | 0.003 | -0.006 | $0.020^{**}$ | $0.018^{**}$ |
| | (-1.81) | (-2.40) | (0.73) | (-1.11) | (0.96) | (-1.39) | (2.54) | (2.14) |
| $\text{Market-to-Book}_{t-1}$ | $-0.023^{***}$ | $-0.018^{***}$ | $-0.016^{***}$ | $-0.015^{**}$ | $-0.023^{***}$ | -0.010 | $0.059^{***}$ | $0.074^{***}$ |
| | (-7.43) | (-3.27) | (-3.91) | (-2.44) | (-6.08) | (-1.51) | (5.80) | (5.81) |
| $\text{Return Volatility}_{t-1}$ | $0.654^{***}$ | $0.362^{***}$ | 0.021 | -0.095 | $-1.960^{***}$ | $-1.812^{***}$ | $-1.385^{***}$ | $-0.835^{**}$ |
| | (7.51) | (2.94) | (0.12) | (-0.41) | (-9.68) | (-7.06) | (-3.74) | (-2.13) |
| Rating FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 25111 | 23774 | 25111 | 23774 | 25111 | 23774 | 25111 | 23774 |
| Adjusted $R^2$ | 0.226 | 0.369 | 0.363 | 0.499 | 0.282 | 0.415 | 0.381 | 0.511 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

### Table 2.5: Matched sample regressions

This table provides results of linear regressions of the logarithm of all-in-drawn loan spread (Spread) and the total cost of borrowing (TCB) on a dummy variable indicating whether a loan is extended by foreign or domestic banks and control variables. In columns (1) and (5), I apply the coarsened exact matching (CEM) algorithm of Iacus et al. (2012) on borrowers' total assets and leverage to reduce the imbalance between observations which are among the loan extended by foreign banks (treated) and those that are not (untreated). In columns (3) and (7), I match on total assets, leverage, profitability, market-to-book, current ratio, and return volatility. Columns (2), (4), (6), and (8) shows the results for firm fixed effects instead of rating and industry fixed effects. Matching on all borrower characteristics does not yield enough observations for meaningful statistical inference. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign | 0.079$^{***}$ | 0.062$^{***}$ | 0.129$^{***}$ | 0.127$^{***}$ | 0.060$^{***}$ | 0.035 | 0.138$^{***}$ | 0.120$^{**}$ |
| | (4.39) | (2.62) | (3.30) | (2.77) | (3.45) | (1.48) | (3.81) | (2.35) |
| Borrower Char. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 24590 | 23275 | 1504 | 1210 | 14404 | 13486 | 949 | 701 |
| Adjusted $R^2$ | 0.553 | 0.679 | 0.659 | 0.828 | 0.794 | 0.850 | 0.812 | 0.886 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

## Table 2.6: Average treatment effect for alternative matching estimators

This table provides matching results for the different set of control variables and numbers of neighbors. The variable of interest is the average treatment effect on the treated of loans extended by foreign banks. In Panel A, I apply nearest neighbor matching including the bias-adjustment of Abadie and Imbens (2006, 2011) to correct for the bias that arises due to the use of continuous control variables. In Panel B, I apply propensity score matching including standard errors derived in Abadie and Imbens (2016) to account for the fact that the propensity score is an estimated quantity. I use a probit model to estimate propensity scores. I drop observations if they violate the overlap assumption for a specific model. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

**Panel A: Nearest Neighbor Matching**

| | Log(Spread) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Foreign | 0.241*** | 0.0739*** | 0.183*** | 0.0838*** |
| | (10.02) | (3.68) | (10.67) | (5.42) |
| Borrower Characteristics | Yes | Yes | Yes | Yes |
| Loan Features | No | Yes | No | Yes |
| Neighbors | 1 | 1 | 10 | 10 |
| Observations | 25111 | 25111 | 25111 | 24655 |

**Panel B: Propensity Score Matching**

| | Log(Spread) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Foreign | 0.346*** | 0.113*** | 0.210*** | 0.159*** |
| | (11.73) | (4.48) | (10.92) | (8.80) |
| Borrower Characteristics | Yes | Yes | Yes | Yes |
| Loan Features | No | Yes | No | Yes |
| Neighbors | 1 | 1 | 10 | 10 |
| Observations | 25111 | 25111 | 25111 | 25111 |

## Table 2.7: Exploring within-firm variation

This table provides results for linear regressions of all-in-drawn loan spread (Spread) and of total cost of borrowing (TCB) on foreign arranger dummy and control variables by using a sample of firms that borrow from both domestic and foreign banks during the sample period. The dependent variable is either the logarithm of Spread or TCB whereas the key explanatory variable is the foreign dummy. The sample is based on firms that borrow from both domestic and foreign banks in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign | 0.108*** | 0.127*** | 0.156*** | 0.128* | 0.043** | 0.039* | 0.039** | 0.107** |
| | (2.70) | (3.24) | (3.70) | (1.88) | (2.12) | (1.91) | (2.26) | (2.40) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Industry FE | Yes | No | No | No | Yes | No | No | No |
| Year FE | Yes | No | No | No | Yes | No | No | No |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | No | Yes | Yes | No | No | Yes | Yes | No |
| Borrower FE | No | No | Yes | No | No | No | Yes | No |
| Borrower x Year FE | No | No | No | Yes | No | No | No | Yes |
| Observations | 4667 | 4657 | 4850 | 3523 | 3130 | 3114 | 3555 | 2043 |
| Adjusted $R^2$ | 0.633 | 0.647 | 0.681 | 0.821 | 0.825 | 0.834 | 0.834 | 0.909 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

### Table 2.8: Real effects of cross-border borrowing

This table shows the effects of the cross-border borrowing on changes in corporate policies of firms and ex-post performance. In Panel A, I examine the effect of foreign loans on borrowers' foreign income, the probability of becoming multinational, and participation in cross-border M&A. In Panel B, I examine the effect of foreign loans on borrowers' profitability, investment, sales growth, and changes in credit rating. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. All regressions include borrower characteristics, and borrower and year fixed effects. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

**Panel A: Changes in Borrowers' Policies**

| | Foreign Income | Multinational | Cross-Border M&A |
|---|---|---|---|
| | (1) | (2) | (3) |
| Foreign | 0.094** | 0.082*** | 0.061*** |
| | (2.18) | (7.59) | (3.00) |
| Borrower Char. | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Borrower FE | Yes | Yes | Yes |
| Observations | 43045 | 56827 | 18917 |
| Adjusted $R^2$ | 0.869 | 0.760 | 0.375 |
| Cluster Variable | Firm | Firm | Firm |

**Panel B: Changes in Ex-post Performance**

| | Profitability | Investment | Sales | Rating |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Foreign | 0.004* | 0.001 | 0.034** | 0.023 |
| | (1.90) | (0.77) | (2.11) | (0.36) |
| Borrower Char. | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Borrower FE | Yes | Yes | Yes | Yes |
| Observations | 102886 | 102124 | 102887 | 40328 |
| Adjusted $R^2$ | 0.523 | 0.661 | 0.956 | 0.830 |
| Cluster Variable | Firm | Firm | Firm | Firm |

### Table 2.9: Announcement returns around loan origination

This table presents the daily stock price response around loan origination of U.S. borrowers with available bank loan data from 1987 to 2016. Panel A reports summary statistics of the cumulative market-model adjusted return for foreign and domestic bank borrowers during the respective interval in percentages. Market beta is estimated over the [-260, -20] period relative to loan origination, requiring at least 100 daily observations. I report CARs over six event windows: (-1, 0), (0, +1), (-1, +1), (-2, +2), (-3, +3), and (-5, +5). Panel B presents the results of regressions of cumulative announcement returns around loan origination on lender type. Heteroscedasticity robust $t$-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

**Panel A: Cumulative abnormal returns of foreign vs. domestic bank borrowers**

| | Foreign Loans (1) | | | | Domestic Loans (2) | | | | Difference (2)-(1) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Median | SD | N | Mean | Median | SD | Diff. | (t-stat) |
| CAR (-1, 0) | 1,929 | 0.04 | -0.06 | 3.81 | 21,255 | 0.13*** | -0.01 | 4.09 | 0.09 | (1.02) |
| CAR (0, +1) | 1,929 | 0.05 | -0.07 | 4.05 | 21,255 | 0.29*** | 0.09 | 4.33 | 0.24* | (2.49) |
| CAR (-1, +1) | 1,929 | 0.06 | -0.14 | 4.87 | 21,255 | 0.30*** | 0.09 | 5.10 | 0.24* | (2.02) |
| CAR (-2, +2) | 1,929 | 0.06 | -0.08 | 6.33 | 21,255 | 0.42*** | 0.11 | 6.49 | 0.36* | (2.38) |
| CAR (-3, +3) | 1,929 | 0.12 | -0.17 | 7.45 | 21,255 | 0.39*** | 0.08 | 7.54 | 0.27 | (1.53) |
| CAR (-5, +5) | 1,929 | 0.07 | -0.33 | 8.84 | 21,255 | 0.32*** | 0.07 | 9.30 | 0.25 | (1.18) |

**Panel B: Foreign banks and abnormal return**

| | CAR (-1, +1) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Foreign | -0.235** | -0.204* | -0.202* | -0.106 | -0.094 |
| | (-2.02) | (-1.75) | (-1.73) | (-0.65) | (-0.58) |
| Borrower Characteristics | No | Yes | Yes | Yes | Yes |
| Loan Features | No | No | Yes | Yes | Yes |
| Borrower FE | No | No | No | Yes | Yes |
| Year FE | No | No | No | No | Yes |
| Observations | 23184 | 23184 | 23184 | 21869 | 21869 |
| Adjusted $R^2$ | 0.001 | 0.001 | 0.002 | 0.185 | 0.186 |

## Table 2.10: The effect of geographic and cultural distance on loan pricing

This table presents results for linear regressions of the logarithm of all-in-drawn loan spread (Spread) on physical and cultural distance, loan features, and borrower characteristics. The dependent variable is the logarithm of Spread. The key explanatory variables are physical and cultural distance. *Physical distance* is the spherical distance between the lead lender and the borrower. *Cultural distance* is the Euclidean distance between the cultures of the borrower's and the lead bank's countries as in Giannetti and Yafeh (2012). The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Physical Distance | 0.035*** | | 0.009 | 0.037** | | 0.033 |
| | (2.83) | | (0.31) | (2.55) | | (0.95) |
| Cultural Distance | | 0.060*** | 0.048 | | 0.055** | 0.006 |
| | | (2.92) | (1.02) | | (2.34) | (0.11) |
| $\text{Log(Amount)}_t$ | -0.054*** | -0.054*** | -0.054*** | -0.085*** | -0.085*** | -0.085*** |
| | (-6.51) | (-6.51) | (-6.51) | (-10.85) | (-10.86) | (-10.87) |
| $\text{Log(Maturity)}_t$ | 0.011 | 0.010 | 0.010 | 0.012 | 0.012 | 0.012 |
| | (0.83) | (0.81) | (0.81) | (0.87) | (0.87) | (0.87) |
| $\text{Number of Lenders}_t$ | -0.007*** | -0.007*** | -0.007*** | -0.006*** | -0.006*** | -0.006*** |
| | (-6.30) | (-6.32) | (-6.32) | (-4.25) | (-4.27) | (-4.26) |
| $\text{Secured}_t$ | 0.375*** | 0.375*** | 0.375*** | 0.284*** | 0.285*** | 0.284*** |
| | (25.69) | (25.69) | (25.69) | (17.10) | (17.12) | (17.10) |
| $\text{Financial Covenants}_t$ | 0.043*** | 0.044*** | 0.044*** | 0.042*** | 0.043*** | 0.043*** |
| | (2.96) | (2.99) | (2.99) | (2.64) | (2.67) | (2.65) |
| $\text{Prime Base Rate}_t$ | -0.022 | -0.022 | -0.022 | 0.012 | 0.012 | 0.012 |
| | (-1.43) | (-1.44) | (-1.43) | (0.75) | (0.73) | (0.74) |
| $\text{Performance Pricing}_t$ | -0.025* | -0.025* | -0.025* | -0.041*** | -0.042*** | -0.041*** |
| | (-1.79) | (-1.79) | (-1.78) | (-2.97) | (-2.98) | (-2.97) |
| $\text{Log(Total Assets)}_{t-1}$ | -0.010 | -0.010 | -0.010 | -0.053*** | -0.053*** | -0.053*** |
| | (-1.12) | (-1.13) | (-1.13) | (-4.21) | (-4.23) | (-4.22) |
| $\text{Leverage}_{t-1}$ | 0.448*** | 0.448*** | 0.448*** | 0.410*** | 0.409*** | 0.410*** |
| | (16.25) | (16.20) | (16.21) | (10.66) | (10.65) | (10.65) |
| $\text{Profitability}_{t-1}$ | -0.440*** | -0.439*** | -0.439*** | -0.662*** | -0.662*** | -0.662*** |
| | (-7.39) | (-7.37) | (-7.37) | (-7.98) | (-7.97) | (-7.98) |
| $\text{Tangibility}_{t-1}$ | -0.054* | -0.055* | -0.055* | -0.211*** | -0.211*** | -0.211*** |
| | (-1.81) | (-1.84) | (-1.84) | (-2.68) | (-2.68) | (-2.68) |
| $\text{Current Ratio}_{t-1}$ | -0.002 | -0.002 | -0.002 | 0.005 | 0.005 | 0.005 |
| | (-0.55) | (-0.55) | (-0.55) | (0.88) | (0.88) | (0.87) |
| $\text{Market-to-Book}_{t-1}$ | -0.052*** | -0.052*** | -0.052*** | -0.057*** | -0.057*** | -0.057*** |
| | (-8.20) | (-8.24) | (-8.23) | (-6.02) | (-6.03) | (-6.02) |
| $\text{Return Volatility}_{t-1}$ | 1.724*** | 1.730*** | 1.729*** | 1.614*** | 1.616*** | 1.613*** |
| Rating FE | Yes | Yes | Yes | No | No | No |
| Industry FE | Yes | Yes | Yes | No | No | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower FE | No | No | No | Yes | Yes | Yes |
| Observations | 25111 | 25107 | 25107 | 23774 | 23772 | 23772 |
| Adjusted $R^2$ | 0.502 | 0.502 | 0.502 | 0.650 | 0.650 | 0.650 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm |

## Table 2.11: The effect of lending relationships on loan pricing

This table provides results for linear regressions of measures of loan pricing on foreign arranger dummy and control variables with a focus on bank relationship variables. The dependent variable is either the logarithm of loan spreads in columns (1)-(4) or the logarithm the total cost of borrowing (TCB) in columns (5)-(8). The key explanatory variables are the interaction terms of foreign dummy with variables related to the relationship between a borrower and a lender. In columns (1) and (5), the relevant variable is a dummy which indicates whether a borrower and a lender interact for the first time in a given deal (*New Relation*). In columns (2) and (6), the relevant variable is a dummy which indicates whether a borrower and a lender interacted in the last five years before a deal (*Old Relation (Dummy)*). In columns (3) and (7), I use the share of the number of loans between a borrower and a lender as a fraction of the total number of loans of a borrower in the last five years before a deal (*Old Relation (Number)*). In columns (4) and (8), I use the share of the loan amount between a borrower and a lender as a fraction of the total loan amount of a borrower in the last five years before a deal (*Old Relation (Amount)*). The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

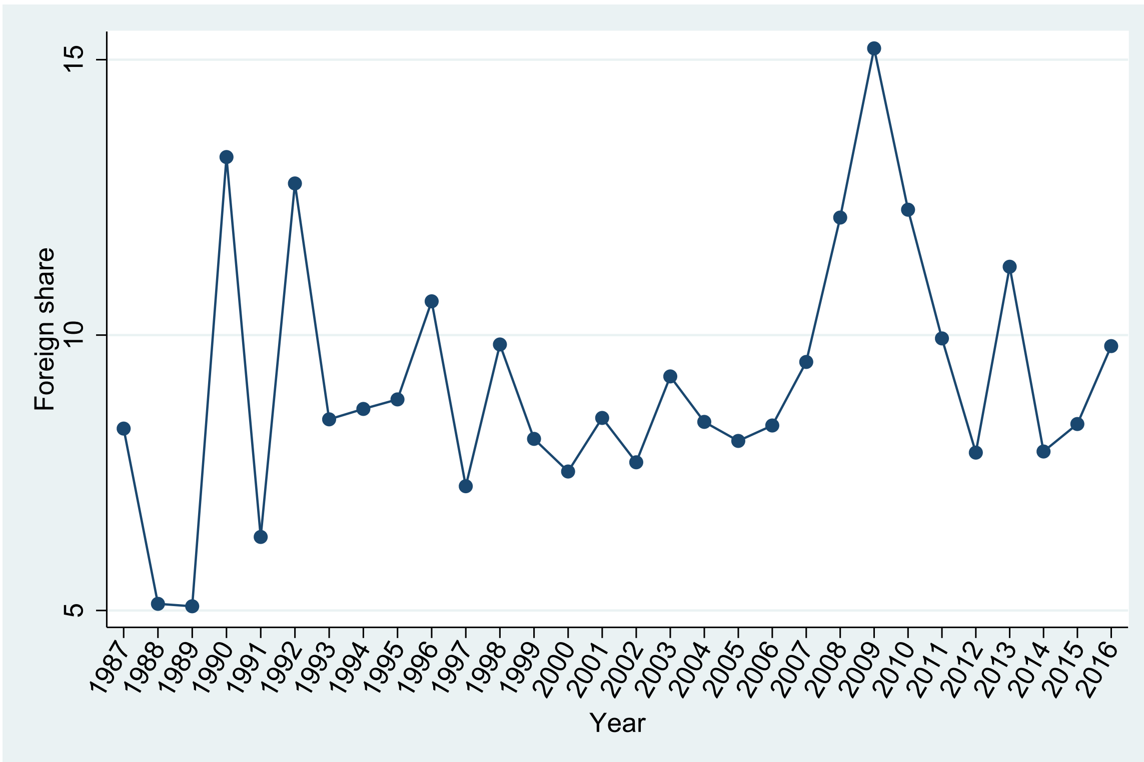
| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign * New Relationship | -0.015 | | | | 0.017 | | | |
| | (-0.47) | | | | (0.53) | | | |
| Foreign * Old Relationship (Dummy) | | 0.019 | | | | -0.011 | | |
| | | (0.60) | | | | (-0.35) | | |
| Foreing * Old Relationship (Number) | | | 0.080* | | | | -0.010 | |
| | | | (1.78) | | | | (-0.23) | |
| Foreign * Old Relationship (Amount) | | | | 0.087** | | | | 0.013 |
| | | | | (2.04) | | | | (0.31) |
| Foreign | 0.088*** | 0.073*** | 0.048** | 0.046* | 0.057** | 0.071*** | 0.064*** | 0.058*** |
| | (3.24) | (3.36) | (2.01) | (1.91) | (2.23) | (3.42) | (2.94) | (2.67) |
| New Relationship | 0.037*** | | | | 0.019** | | | |
| | (3.60) | | | | (2.04) | | | |
| Old Relationship Dummy | | -0.026** | | | | -0.011 | | |
| | | (-2.56) | | | | (-1.19) | | |
| Old Relationship (Number) | | | -0.048*** | | | | -0.037*** | |
| | | | (-3.57) | | | | (-3.03) | |
| Old Relationship (Amount) | | | | -0.049*** | | | | -0.034*** |
| | | | | (-3.71) | | | | (-2.86) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 20412 | 20412 | 18304 | 18304 | 12481 | 12481 | 11402 | 11402 |
| Adjusted $R^2$ | 0.551 | 0.551 | 0.559 | 0.557 | 0.803 | 0.803 | 0.807 | 0.807 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

# Appendix A: Additional figures and tables

**Figure A1: Share of foreign bank loan volume over years**

This figure presents the share of foreign bank in total bank lending over the period 1987-2016.

Share of foreign bank loan volume



### Table A1: Number and value of loans by foreign banks' countries over the period 1987-2016

This table provides a break down of loans by foreign-bank country. The first column lists the name of the bank country. The second column presents the number of banks. The third column presents the number of loans. The fourth column shows the fraction of total number of loans accounted for by the bank country. The fifth column presents the total nominal transaction value in millions of US dollar by bank country. The final column shows the fraction of total volume of loans accounted for by the bank country.

| Country | Number of banks | Number of loans | Percentange (number) | Amount of loans(mm) | Percentange (value) |
|---|---|---|---|---|---|
| Canada | 23 | 707 | 33.428 | 163495.953 | 32.906 |
| Switzerland | 8 | 308 | 14.563 | 96845.359 | 19.492 |
| France | 15 | 307 | 14.515 | 63054.730 | 12.691 |
| Germany | 8 | 228 | 10.780 | 81629.031 | 16.429 |
| United Kingdom | 31 | 189 | 8.936 | 43909.488 | 8.838 |
| Netherlands | 12 | 151 | 7.139 | 23750.576 | 4.780 |
| Japan | 26 | 80 | 3.783 | 11881.688 | 2.391 |
| Norway | 7 | 39 | 1.844 | 3021.164 | 0.608 |
| Austria | 3 | 20 | 0.946 | 402.800 | 0.081 |
| China | 5 | 14 | 0.662 | 560.250 | 0.113 |
| Australia | 5 | 10 | 0.473 | 878.720 | 0.177 |
| Hong Kong | 5 | 7 | 0.331 | 106.730 | 0.021 |
| Luxembourg | 2 | 6 | 0.284 | 1861.712 | 0.375 |
| Korea (South) | 5 | 6 | 0.284 | 327.000 | 0.066 |
| Belgium | 4 | 6 | 0.284 | 1186.161 | 0.239 |
| Ireland | 3 | 5 | 0.236 | 1019.800 | 0.205 |
| Brazil | 1 | 4 | 0.189 | 117.750 | 0.024 |
| Taiwan | 3 | 3 | 0.142 | 122.000 | 0.025 |
| Sweden | 2 | 3 | 0.142 | 7.507 | 0.002 |
| Portugal | 1 | 3 | 0.142 | 1800.000 | 0.362 |
| Italy | 1 | 3 | 0.142 | 6.959 | 0.001 |
| Singapore | 2 | 2 | 0.095 | 267.500 | 0.054 |
| Denmark | 1 | 2 | 0.095 | 95.794 | 0.019 |
| Bahrain | 1 | 2 | 0.095 | 56.000 | 0.011 |
| Thailand | 1 | 1 | 0.047 | 4.000 | 0.001 |
| Spain | 1 | 1 | 0.047 | 75.000 | 0.015 |
| South Africa | 1 | 1 | 0.047 | 25.000 | 0.005 |
| Russia | 1 | 1 | 0.047 | 6.000 | 0.001 |
| Mexico | 1 | 1 | 0.047 | 75.000 | 0.015 |
| Malaysia | 1 | 1 | 0.047 | 44.600 | 0.009 |
| Israel | 1 | 1 | 0.047 | 10.000 | 0.002 |
| Iceland | 1 | 1 | 0.047 | 4.000 | 0.001 |
| Hungary | 1 | 1 | 0.047 | 4.600 | 0.001 |
| Finland | 1 | 1 | 0.047 | 200.000 | 0.040 |
| Total | 184 | 2115 | 100 | 496852.8739 | 100 |

### Table A2: Foreign banks and different financing cost components

This table provides results of linear regressions of individual components of the total cost of borrowing on foreign arranger dummy and control variables. It shows the results for upfront fees, commitment fees, and facility fees. All dependent variables are log-transformed. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Upfront Fee) | | Log(Commitment Fee) | | Log(Facility Fee) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Foreign | 0.191*** | 0.080 | 0.182*** | 0.120*** | -0.068 | -0.053 |
| | (3.43) | (1.55) | (9.87) | (7.73) | (-1.06) | (-0.89) |
| Loan Features | No | Yes | No | Yes | No | Yes |
| Borrower Characteristics | No | Yes | No | Yes | No | Yes |
| Rating FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes | No | Yes |
| Year FE | No | Yes | No | Yes | No | Yes |
| Loan Type FE | No | Yes | No | Yes | No | Yes |
| Loan Purpose FE | No | Yes | No | Yes | No | Yes |
| Observations | 6188 | 6188 | 11988 | 11988 | 4018 | 4018 |
| Adjusted $R^2$ | 0.031 | 0.302 | 0.153 | 0.377 | 0.292 | 0.457 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm |

### Table A3: Rating groups

This table presents subsample results for rated vs. unrated and investment grade vs. non-investment grade firms. The dependent variable is the logarithm of all-in-drawn loan spread (Spread). The key explanatory variable is *foreign*, which is a dummy variable that equals one if the lender is a foreign bank, and zero otherwise. Columns (1) and (2) show results for the subsamples of rated firms, columns (3) and (4) show results for the subsamples of unrated firms, columns (5) and (6) show results for the subsamples of investment grade firms, and columns (7) and (8) show results for the subsamples of non-investment grade firms. The sample is based on loans in the US syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, Compustat, and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | **Rated** Log(Spread) | | **Unrated** Log(Spread) | | **Inv. grade** Log(Spread) | | **Junk** Log(Spread) | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign | 0.050** | 0.042 | 0.098*** | 0.090** | 0.042 | 0.157 | 0.045** | 0.049 |
| | (2.15) | (1.31) | (3.75) | (2.55) | (0.47) | (1.37) | (2.15) | (1.62) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | No | No | No | Yes | No | Yes | No |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 10284 | 9948 | 14827 | 13457 | 2048 | 1945 | 8236 | 7909 |
| Adjusted $R^2$ | 0.673 | 0.734 | 0.333 | 0.594 | 0.698 | 0.787 | 0.580 | 0.662 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

## Table A4: Impact of foreign banks on pricing of credit lines and term loans

This table provides results of linear regressions of all-in-drawn loan spread (Spread) and total cost of borrowing (TCB), and the two most commonly used fee types-facility and upfront fee-on foreign lead arranger dummy and the credit line dummy. I only look at loans that can be classified as either credit line or term loans. Including the loan type fixed effects leads to omission of the credit line dummy in columns (2), (4), (6), and (8). All dependent variables are log-transformed. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | Log(TCB) | | Log(Facility Fee) | | Log(Upfront Fee) | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign | 0.078** | 0.089*** | -0.003 | 0.025 | -0.178 | -0.134 | -0.018 | -0.012 |
| | (2.55) | (3.62) | (-0.08) | (0.97) | (-0.99) | (-0.89) | (-0.25) | (-0.17) |
| Foreign * Credit Line | 0.031 | -0.014 | 0.112*** | 0.054** | 0.115 | 0.095 | 0.302*** | 0.196*** |
| | (0.94) | (-0.52) | (3.36) | (2.04) | (0.67) | (0.67) | (3.84) | (2.68) |
| Credit Line | -0.386*** | - | -1.062*** | - | -0.151*** | - | -0.430*** | - |
| | (-31.44) | | (-83.25) | | (-2.68) | | (-16.24) | |
| Foreign + Foreign * Credit Line | 0.109*** | 0.075*** | 0.109*** | 0.079*** | -0.063 | -0.039 | 0.284*** | 0.184*** |
| | (15.00) | (13.68) | (16.18) | (21.11) | (1.23) | (0.52) | (20.47) | (11.51) |
| Loan Features | No | Yes | No | Yes | No | Yes | No | Yes |
| Borrower Characteristics | No | Yes | No | Yes | No | Yes | No | Yes |
| Rating FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Year FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Loan Type FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Loan Purpose FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 25111 | 25111 | 14555 | 14555 | 4018 | 4018 | 6188 | 6188 |
| Adjusted $R^2$ | 0.279 | 0.504 | 0.616 | 0.794 | 0.295 | 0.455 | 0.068 | 0.310 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

### Table A5: Covariate imbalances before and after coarsened exact matching

This table reports measures of imbalance before and after applying the coarsened exact matching (CEM) algorithm of Iacus et al. (2012). $\mathcal{L}_1$ measures the unidimensional imbalance between loans extended by foreign banks (treated) and domestic loans (untreated) where $\mathcal{L}_1$ is bounded between zero and one. A lower $\mathcal{L}_1$ statistic indicates a lower imbalance. I also report differences in means and medians between treated and untreated groups. CEM (1) refers to matching on total assets and leverage. CEM (2) refers to matching on total assets, leverage, profitability, market-to-book, current ratio, and return volatility. Matching on all borrower characteristics does not yield enough observations for meaningful statistical inference. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan and Compustat, respectively. I define all variables in Appendix C.

| | Before CEM | | | After CEM (1) | | | After CEM (2) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\mathcal{L}_1$ | ΔMean | ΔMedian | $\mathcal{L}_1$ | ΔMean | ΔMedian | $\mathcal{L}_1$ | ΔMean | ΔMedian |
| Log(Total Assets) | 0.153 | 0.375 | 0.411 | 0.128 | 0.346 | 0.384 | 0.119 | -0.167 | -0.240 |
| Leverage | 0.139 | 0.052 | 0.052 | 0.145 | 0.057 | 0.052 | 0.120 | -0.000 | -0.008 |
| Profitability | 0.075 | 0.002 | -0.003 | 0.070 | 0.001 | -0.003 | 0.112 | -0.000 | -0.003 |
| Tangibility | 0.133 | 0.049 | 0.057 | 0.134 | 0.048 | 0.057 | 0.090 | 0.011 | 0.026 |
| Current Ratio | 0.115 | -0.165 | -0.236 | 0.132 | -0.179 | -0.250 | 0.096 | 0.025 | -0.112 |
| Market-to-Book | 0.068 | 0.003 | 0.004 | 0.069 | 0.010 | 0.011 | 0.070 | 0.065 | 0.012 |
| Return Volatility | 0.075 | -0.003 | -0.001 | 0.071 | -0.002 | -0.001 | 0.000 | 0.001 | 0.001 |

## Table A6: Foreign banks lending during the 2008-2009 crisis

This table provides results for linear regressions of measures of loan pricing on foreign arranger dummy and control variables with a focus on crisis variable. The dependent variable is logarithm of either all-in-drawn loan spread (Spread) or the total cost of borrowing (TCB). The key explanatory variables are the foreign dummy and crisis. *Crisis* is a dummy variable equals to one for the years of 2008 and 2009, and zero otherwise. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | Log(TCB) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Crisis * Foreign | -0.013 | -0.128* | 0.096 | -0.024 |
| | (-0.20) | (-1.84) | (1.41) | (-0.25) |
| Foreign | 0.050** | 0.037 | 0.028 | 0.021 |
| | (2.25) | (1.36) | (1.50) | (0.82) |
| Crisis | 0.373*** | 0.287*** | 0.239*** | 0.213*** |
| | (16.27) | (11.77) | (11.15) | (8.19) |
| Loan Features | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes |
| Rating FE | Yes | No | Yes | No |
| Industry FE | Yes | No | Yes | No |
| Loan Type FE | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes |
| Observations | 25111 | 23774 | 14555 | 13627 |
| Adjusted $R^2$ | 0.411 | 0.575 | 0.762 | 0.819 |
| Cluster Variable | Firm | Firm | Firm | Firm |

### Table A7: Foreign banks lending during the periods of tightening in credit standards

This table presents results when credit market conditions are tight versus loose (determined based on the Federal Reserve's senior loan officer survey on bank lending practices). The dependent variable is the logarithm of all-in-drawn loan spread (Spread) or of total cost of borrowing (TCB). The key explanatory variables are the foreign dummy and tightening. *Tightening* is determined by the net % of loan officers that report tightening in credit standards at the time of loan origination. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, Compustat, and CRSP, respectively. I define all variables in Appendix C. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign * Tightening | -0.000 | -0.000 | -0.000 | -0.000 | 0.001 | 0.001 | 0.000 | 0.001 |
| | (-0.32) | (-0.07) | (-0.37) | (-0.01) | (0.73) | (1.04) | (0.42) | (0.56) |
| Foreign | 0.089*** | 0.090*** | 0.078*** | 0.080*** | 0.062*** | 0.062*** | 0.054*** | 0.053*** |
| | (4.90) | (4.98) | (3.25) | (3.41) | (3.54) | (3.62) | (3.37) | (3.41) |
| Tightening | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.002* | 0.002* |
| | (3.02) | (2.97) | (3.18) | (3.06) | (3.24) | (3.05) | (2.07) | (2.03) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Industry FE | Yes | No | No | No | Yes | No | No | No |
| Year FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Borrower FE | No | No | Yes | Yes | No | No | Yes | Yes |
| Observations | 23761 | 23754 | 22497 | 22487 | 13883 | 13872 | 12990 | 12975 |
| Adjusted $R^2$ | 0.519 | 0.523 | 0.662 | 0.666 | 0.798 | 0.800 | 0.853 | 0.855 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

### Table A8: Foreign banks and multinational firms

This table provides results for linear regressions of measures of loan pricing on foreign arranger dummy and control variables with a focus on multinational variable. The dependent variable is the logarithm of all-in-drawn loan spread (Spread) or of total cost of borrowing (TCB). The key explanatory variables are the interaction terms of foreign arranger dummy with multinational dummy variable. *Multinational* is a dummy variable which indicates whether a borrower is a multinational or pure domestic firm. A firm is defined as a multinational if any of its foreign pretax income (Compustat item: PIFO) or foreign income tax (Compustat item: TXFO) is not missing in at least one year over the previous three years. The sample is based on loans in the US syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | Log(TCB) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Foreign * Multinational | -0.056 | -0.059* | -0.001 | -0.011 | -0.009 | 0.010 |
| | (-1.61) | (-1.71) | (-0.03) | (-0.33) | (-0.26) | (0.23) |
| Foreign | 0.109*** | 0.113*** | 0.062** | 0.061** | 0.060** | 0.027 |
| | (4.45) | (4.72) | (2.08) | (2.51) | (2.50) | (1.08) |
| Multinational | -0.046*** | -0.046*** | -0.050*** | -0.040*** | -0.040*** | -0.044*** |
| | (-3.58) | (-3.54) | (-2.61) | (-3.51) | (-3.51) | (-3.24) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | Yes | No | Yes | Yes | No |
| Industry FE | Yes | No | No | Yes | No | No |
| Year FE | Yes | No | No | Yes | No | No |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | No | Yes | Yes | No | Yes | Yes |
| Borrower FE | No | No | Yes | No | No | Yes |
| Observations | 25111 | 25104 | 23765 | 14555 | 14540 | 13609 |
| Adjusted $R^2$ | 0.506 | 0.511 | 0.660 | 0.794 | 0.796 | 0.852 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm |

## Table A9: Participant banks

This table provides results for linear regressions of measures of loan pricing and fees on foreign dummy and control variables with a focus on foreign participant variable. The dependent variable is the logarithm of all-in-drawn loan spread (Spread), total cost of borrowing (TCB), upfront fees, commitment fees, or facility fees. The key explanatory variables are the foreign dummy and foreign participants (Part). *Part* is a variable which indicates the fraction of foreign participant banks. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The loan and borrower characteristics are obtained from Dealscan, and Compustat and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | Log(TCB) | | Log(Upfront Fee) | | Log(Commitment Fee) | | Log(Facility Fee) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Foreign * Part | -0.089 | 0.040 | -0.129** | -0.021 | -0.308* | -0.192 | -0.038 | 0.097 | -0.082 | -0.099 |
| | (-1.43) | (0.52) | (-1.98) | (-0.28) | (-1.73) | (-0.74) | (-0.62) | (1.16) | (-0.32) | (-0.27) |
| Foreign | 0.119*** | 0.062* | 0.107*** | 0.062* | 0.214** | 0.175 | 0.120*** | 0.032 | 0.026 | -0.034 |
| | (4.41) | (1.68) | (3.90) | (1.68) | (2.46) | (1.20) | (5.35) | (0.87) | (0.20) | (-0.18) |
| Part | -0.045* | -0.128*** | 0.048** | -0.054* | 0.243*** | 0.341** | 0.095*** | 0.059* | 0.168*** | 0.093 |
| | (-1.70) | (-4.06) | (2.10) | (-1.78) | (2.91) | (2.47) | (3.92) | (1.81) | (3.34) | (1.33) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Char. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 18208 | 17498 | 11470 | 10823 | 3400 | 2656 | 8651 | 7543 | 3205 | 2763 |
| Adjusted $R^2$ | 0.625 | 0.718 | 0.808 | 0.858 | 0.344 | 0.573 | 0.471 | 0.602 | 0.521 | 0.740 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

## Table A10: Canadian vs. European Banks

This table presents subsample results for Canadian and European banks. The dependent variable is the logarithm of all-in-drawn loan spread (Spread) or of total cost of borrowing (TCB). The key explanatory variable is *foreign*, which is a dummy variable that equals one if the lender is a Canadian bank or a European bank, and zero otherwise. Columns (1)-(4) shows results for foreign banks from Canada whereas columns (5)-(8) shows results for foreign banks from Europe. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, Compustat, and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Foreign Banks from Canada | | | | Foreign Banks from Europe | | | |
|---|---|---|---|---|---|---|---|---|
| | Log(Spread) | | Log(TCB) | | Log(Spread) | | Log(TCB) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign | 0.073** | 0.034 | 0.023 | -0.045 | 0.110*** | 0.094*** | 0.098*** | 0.091*** |
| | (2.48) | (0.78) | (0.76) | (-1.27) | (4.85) | (3.35) | (4.61) | (3.22) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 23703 | 22366 | 13747 | 12826 | 24270 | 22937 | 14070 | 13149 |
| Adjusted $R^2$ | 0.498 | 0.649 | 0.788 | 0.847 | 0.505 | 0.655 | 0.791 | 0.849 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

## Table A11: Commercial vs. Investment Banks

This table presents subsample results for loans from investment vs. commercial banks. The dependent variable is the logarithm of all-in-drawn loan spread (Spread) or of total cost of borrowing (TCB). The key explanatory variables are the foreign dummy and investment bank. *Investment bank* is a dummy variable equal to one if the lender is an investment bank, and zero for a commercial bank. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, Compustat, and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign * Investment Bank | -0.237* | -0.229* | -0.251* | -0.246 | -0.311* | -0.297* | -0.252 | -0.205 |
| | (-1.67) | (-1.67) | (-1.66) | (-1.64) | (-1.82) | (-1.87) | (-1.50) | (-1.20) |
| Foreign | 0.117*** | 0.118*** | 0.098*** | 0.104*** | 0.084*** | 0.085*** | 0.060*** | 0.059*** |
| | (6.21) | (6.43) | (3.98) | (4.33) | (4.82) | (4.95) | (3.09) | (3.03) |
| Investment Bank | 0.272*** | 0.270*** | 0.245*** | 0.249*** | 0.177*** | 0.176*** | 0.174*** | 0.177*** |
| | (15.33) | (15.38) | (11.60) | (11.77) | (11.16) | (11.08) | (7.53) | (7.57) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Industry FE | Yes | No | No | No | Yes | No | No | No |
| Year FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Borrower FE | No | No | Yes | Yes | No | No | Yes | Yes |
| Observations | 25111 | 25104 | 23774 | 23765 | 14555 | 14540 | 13627 | 13609 |
| Adjusted $R^2$ | 0.513 | 0.517 | 0.656 | 0.661 | 0.791 | 0.792 | 0.848 | 0.850 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

## Table A12: Loans initiated by the U.S. branches of foreign banks

This table presents results for linear regressions of the logarithm of all-in-drawn loan spread and of total cost of borrowing on the foreign bank's branches in the U.S., loan features, and borrower characteristics. There are 230 loans extended by U.S. branch of foreign banks to 117 publicly traded U.S. firms during the sample period. The dependent variable is the logarithm of all-in-drawn loan spread (Spread) or of total cost of borrowing (TCB). The key explanatory variable is Foreign Branch, which is a dummy variable that equals one if the lender is a U.S. branch of foreign banks, and zero otherwise. Columns (1) and (5) shows results for the main regression model with rating, industry (two-digit SIC code), year, loan type and loan purpose fixed effects. In columns (2) and (6), I replace industry and year fixed effects by industry-year fixed effects. Columns (3) and (7) shows the results for firm fixed effects instead of rating fixed effects. In columns (4) and (8), I use loan type, loan purpose, and firm-year fixed effects. The sample is based on loans in the U.S. syndicated loan market between 1987 and 2016. The data on loan and borrower characteristics are obtained from Dealscan, Compustat, and CRSP, respectively. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at 10%, 5%, and 1%.

| | Log(Spread) | | | | Log(TCB) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Foreign Branch | 0.077 | 0.067 | 0.004 | 0.008 | 0.025 | 0.021 | 0.036 | 0.264$^{***}$ |
| | (1.57) | (1.35) | (0.06) | (0.05) | (0.60) | (0.51) | (0.87) | (3.08) |
| Loan Features | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Industry FE | Yes | No | No | No | Yes | No | No | No |
| Year FE | Yes | No | No | No | Yes | No | No | No |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | No | Yes | Yes | No | No | Yes | Yes | No |
| Borrower FE | No | No | Yes | No | No | No | Yes | No |
| Borrower x Year FE | No | No | No | Yes | No | No | No | Yes |
| Observations | 22996 | 22988 | 21643 | 12066 | 13324 | 13308 | 12381 | 6317 |
| Adjusted $R^2$ | 0.500 | 0.505 | 0.660 | 0.810 | 0.791 | 0.793 | 0.852 | 0.912 |

## Table A13: Loans initiated by U.S. banks to foreign firms

This table presents results for loans lend by U.S. banks in foreign market. There are total 532 loans initiated by U.S. banks to foreign firms (205 firms). Among these loans, 223 are borrowed by European firms (81 firms). The dependent variable is the logarithm of all-in-drawn loan spread (Spread). The key explanatory variable is *foreign*, which is a dummy variable that equals one if the lender is a foreign bank, and zero otherwise. Columns (1)-(4) shows results for all loans initiated by U.S. banks to foreign countries whereas columns (5)-(8) shows results for loans initiated by U.S. banks to European firms. The sample covers the period between 1987 and 2016. The data on loan is obtained from Dealscan. I define all variables in Appendix C. $t$-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

| | All Countries | | | | European Countries | | | |
|---|---|---|---|---|---|---|---|---|
| | Log(Spread) | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\text{Foreign}_k$ | 0.284*** | 0.333*** | 0.206** | 0.214** | 0.218** | 0.152 | 0.185 | 0.142 |
| | (3.52) | (4.16) | (1.98) | (2.01) | (2.11) | (1.29) | (1.42) | (1.10) |
| $\text{Log(Amount)}_t$ | -0.196*** | -0.208*** | -0.226*** | -0.151*** | -0.187*** | -0.189*** | -0.191*** | -0.150*** |
| | (-7.52) | (-7.16) | (-7.50) | (-6.12) | (-5.67) | (-4.70) | (-5.77) | (-3.77) |
| $\text{Log(Maturity)}_t$ | 0.154** | 0.043 | 0.167** | 0.255*** | 0.351*** | 0.361*** | 0.220** | 0.370*** |
| | (2.18) | (0.67) | (2.25) | (3.73) | (3.12) | (3.63) | (2.01) | (3.54) |
| $\text{Number of Lenders}_t$ | -0.012* | -0.013** | -0.012** | -0.016*** | -0.015** | -0.019*** | -0.021*** | -0.017* |
| | (-1.85) | (-2.37) | (-2.07) | (-2.76) | (-2.30) | (-3.58) | (-3.46) | (-1.97) |
| $\text{Secured}_t$ | 0.224** | 0.371*** | 0.346*** | 0.219 | 0.409*** | 0.230 | 0.377** | 0.187 |
| | (2.52) | (3.75) | (2.77) | (1.32) | (2.76) | (1.29) | (2.04) | (0.78) |
| $\text{Financial Covenants}_t$ | 0.095 | 0.059 | 0.109 | 0.127 | 0.235 | 0.004 | 0.216 | 0.180 |
| | (0.90) | (0.64) | (0.88) | (1.05) | (1.48) | (0.02) | (1.10) | (0.84) |
| $\text{Prime Base Rate}_t$ | 0.229* | 0.219** | 0.110 | -0.044 | 0.428* | 0.539** | 0.340 | 0.123 |
| | (1.66) | (2.02) | (0.71) | (-0.30) | (1.94) | (2.19) | (1.38) | (0.37) |
| $\text{Performance Pricing}_t$ | -0.142* | -0.246*** | -0.124 | -0.230* | -0.206* | -0.333** | -0.315** | -0.393* |
| | (-1.92) | (-2.76) | (-1.28) | (-1.82) | (-1.73) | (-2.33) | (-2.14) | (-1.69) |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Country FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Year FE | Yes | No | No | No | Yes | No | No | No |
| Industry x Year FE | No | Yes | No | No | No | Yes | No | No |
| Country x Year FE | No | No | Yes | No | No | No | Yes | No |
| Industry x Country x Year FE | No | No | No | Yes | No | No | No | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Purpose FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 808 | 773 | 683 | 544 | 410 | 364 | 357 | 287 |
| Adjusted $R^2$ | 0.627 | 0.717 | 0.751 | 0.866 | 0.702 | 0.801 | 0.758 | 0.857 |
| Cluster Variable | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |

# Appendix B: Total cost of borrowing

Berg et al. (2016) show that the pricing structure of loan commitments is complex and includes a variety of fees. The most important fee types are the spread (interest margin above LIBOR paid on drawn portion of loan), the upfront fee (one-time fee paid at loan closing date), the commitment fee (one-time fee paid on unused loan commitments), and the facility fee (annual fee paid on total committed amount regardless of usage). Importantly, different fees are used to price options embedded in loan contracts. For instance in credit lines, borrowers do not have to pay the committed spread until they actually choose to use the credit line. Furthermore, different fees can be used to screen borrowers' private information about the likelihood of future credit line usage. Lenders, therefore, typically use a combination of these fee types depending on borrower risk and loan type.

The total cost of borrowing (TCB) measure of Berg et al. (2016) reflects the option characteristics of bank loans and takes the likelihood of exercising these options as well as the different fees into account. The measure is defined as

$$
\begin{aligned}
&\text{TCB=Upfront Fee/Expected Loan Maturity in Years} \\
&+ \text{(1-PDD)} \cdot \text{(Facility Fee + Commitment Fee)} \\
&+ \text{PDD} \cdot \text{(Facility Fee + Spread)} \\
&+ \text{PDD} \cdot \text{Prob(Utilization > Utilization Threshold | Usage > 0)} \cdot \text{Utilization Fee} \\
&+ \text{Prob(Cancellation)} \cdot \text{Cancellation Fee,}
\end{aligned}
$$

where PDD is the likelihood that a credit line is used,
Prob(Utilization > Utilization Threshold | Usage > 0) is the probability that the utilization of the credit line is higher than the threshold specified in the contract conditional on observing usage, and Prob(Cancellation) is the probability that the loan will be canceled. I use TCB as the alternative measure of loan pricing.

## Table A14: Appendix C: Definition of Variables

| Variable | Type | Description | Source |
|---|---|---|---|
| *Dependent variables* | | | |
| Spread | Bps. | All-in-drawn spread over LIBOR in basis points. | Dealscan |
| TCB | Bps. | Total Cost of Borrowing (TCB) developed and provided by Berg et al. (2016). The TCB measure reflects option characteristics of loans, differentiates between credit lines and term loans, and takes various fees paid to lenders into account. | Dealscan |
| Upfront Fee | Bps. | Fee paid upon completion of syndicated loan deal. | Dealscan |
| Commitment Fee | Bps. | Fee paid on the unused amount of loan commitments. | Dealscan |
| Facility Fee | Bps. | Fee paid on the total committed amount independent of usage. | Dealscan |
| *Loan-level variables* | | | |
| Amount | $ | Loan amount. | Dealscan |
| Maturity | Months | Maturity of the loan. | Dealscan |
| Secured | Yes/No | An indicator that equals one if the loan is secured, and zero votherwise. | Dealscan |
| Financial Covenants | Yes/No | An indicator that equals one if the loan has financial covenants, and zero otherwise. | Dealscan |
| Performance Pricing | Yes/No | An indicator that equals one if the loan has performance pricing feature, and zero otherwise. | Dealscan |
| Prime Base Rate | Yes/No | An indicator that equals one if the base rate of the loan is prime, and zero otherwise. | Dealscan |
| Number of Lenders | Number | Number of lenders (lead arranger and participants) of a facility as indicated by the Dealscan lender shares table. | Dealscan |
| Foreign Participants | [0-1] | The number of foreign participant as the proportion of total number of participant banks in a syndicate. | Dealscan |
| Lead Share | [0-1] | Share of the loan that is retained by the lead bank at loan origination as indicated by the field BankAllocation in the Dealscan lender shares table. | Dealscan |
| New Relation | Yes/No | Dummy variable equal to one if the lead banks lends to the borrower for the first time. The variable is set to missing for the first loan of each company in the sample. | Dealscan |
| Old Relation (Dummy) | Yes/No | Dummy variable equal to one if the borrower and lender had at least one lending relationship in the last 5 years before loan origination. | Dealscan |
| Old Relation (Number) | [0-1] | Number of loans by bank j to borrower i in the last 5 years before loan origination divided by the total number of loans by borrower i in the last 5 years. | Dealscan |
| Old Relation (Amount) | [0-1] | Amount of loans by bank j to borrower i in the last 5 years before loan origination divided by the total amount of loans by borrower i in the last 5 years. | Dealscan |
| *Group indicators* | | | |
| Foreign | Yes/No | An indicator variable equal to one if the lead lender in the loan syndicate is a foreign lender. A foreign lender is defined as a lender incorporated outside of the United States, excluding a foreign branch of the U.S. banks or a U.S. branch of foreign banks. A lender is defined as a lead lender if "Lead Arranger Credit" is equal to "Yes" in Dealscan, if a lender is identified as "Agent," "Administrative Agent," "Arranger," and "Lead Bank," or if the loan is a sole-lender loan, following Bharath, Dahiya, Saunders, and Srinivasan (2009). | Dealscan |
| Credit Line | Yes/No | Equals one if the loan type is revolving line of credit. | Dealscan |
| Term Loan | Yes/No | Equals one if the loan type is term loan. | Dealscan |
| Not Rated | Yes/No | Equals one if the firm has credit rating at the loan start date. | Compustat |
| Investment Grade | Yes/No | Dummy variable equal to one if the S&P rating is BBB- or higher and missing for non-rated borrowers. | Compustat |
| Multinational | Yes/No | A firm is defined as a multinational if any of its foreign pretax income (Compustat item: PIFO) or foreign income tax (Compustat item: TXFO) is not missing in at least one year over the previous three years. | Compustat |
| Firm-level variables | | | |
| Total Assets | $mn. | Firm's total assets at the latest fiscal period that ended prior to loan start date. | Compustat |
| Leverage | Ratio | The ratio of total book debt to total assets. | Compustat |
| Current ratio | Ratio | The ratio of current assets to current liabilities. | Compustat |
| Profitability | Ratio | The ratio of net income to total assets. | Compustat |
| Tangibility | Ratio | Ratio of property, plant, and equipment to total assets. | Compustat |
| Market-to-Book | | Ratio of book value of assets - book value of equity + market value of equity to book value of assets. | Compustat |
| Return Volatility | Decimal | The standard deviation of stock returns in the quarter prior to loan start date. | CRSP |
| *Additional data* | | | |
| Physical Distance | Log | Geographic distance, which is the Great Circle Distance between foreign lenders and the U.S. borrowers. | mapsofworld.com |
| Cultural Distance | Log | Euclidean distance between the cultures of the borrower's and the lead bank's countries as in Giannetti and Yafeh (2012). | World Values Survey |

# Chapter 3

# Foreign Acquisition and Credit Risk: Evidence from the U.S. CDS Market

## 3.1 Introduction

The United States has become the recipient of Foreign Direct Investment (FDI) in recent decades as foreign corporations purchase U.S. companies or establish new plants on the U.S. soil.[1] According to UNCTAD (2013), over the past decade, foreign direct investment in the United States peaked in 2008, reaching $310 billion. During the recent global economic recession, foreigners dramatically reduced their investment in the U.S. but the trend reversed during the following years. The main driving method behind this surge in FDI has been through cross-border acquisitions which have become a large component of the total U.S. takeover activity (UNCTAD, 2013). A well-known case includes the $3 billion cash injection into Chesapeake Shale by Norway's StatoilHydro in November 2008 in exchange for a 32% stake. The U.S. government has sometimes taken a hostile attitude toward foreign acquisitions of U.S. target firms.[2] For instance, some high profile foreign acquisitions, such as China's Lenovo's purchase of IBM's Thinkpad and India's Tata Motor's 2008 acquisition of Ford's

[1] FDI includes green-field investment in new assets in a foreign country, and acquisition of pre-existing foreign assets.

[2] See the article "Love me, love me not" in the July, 2008 issue of The Economist.

Jaguar and Land Rover divisions, has raised great attention in policy circles.

The objective of this paper is to study how foreign acquisition affects the credit risk and stock volatility. Several studies have previously assessed the beneficial role of foreign ownership in firm-efficiency, productivity, corporate governance, risk-sharing, and liquidity provision. However, evidence on the downside role of foreign acquisitions is scarce. While some studies have shown superior performance of foreign-owned firms, compared to domestically owned firms, (see, e.g., Harris and Ravenscraft, 1991; Doms and Jensen, 1998; Chen, 2011; Chari, Chen, and Dominguez, 2012), there is no evidence on whether the act of foreign block acquisitions increases the credit default premium of the target firms. This paper fills this gap by studying how the creation of sizeable foreign ownership stakes affects the target companies' creditworthiness and their probability of default.

Foreign block acquisition might affect corporate risk through different channels. First, foreign investors are internationally diversified and benefit from international risk-sharing (see, e.g., Obstfeld, 1994; Acemoglu and Zilibotti, 1997; Faccio, Marchica, and Mura, 2011). Second, foreign-acquired firms might experience higher exposure to future cash flow uncertainty, and in turn high level credit risk (Güntay and Hackbarth, 2010; Buraschi, Trojani, and Vedolin, 2013). Third, compared with domestic investors, foreign investors generally face more information asymmetry with the managers (see, e.g., Brennan and Cao, 1997; Hau, 2001; Chan, Menkveld, and Yang, 2008). As a result, they may be less effective monitors. Such features of foreign investors increase target firms' credit risk. On the other hand, foreign ownership is associated with a more effective restructuring of the acquired firms and a higher firm-level efficiency and productivity, which in turn should decrease credit risk (see, e.g., Arnold and Javorcik, 2009; Chari, Chen, and Dominguez, 2012). In the end, how foreign block purchases affect target firm's credit risk is ultimately an empirical question.

I use a newly-constructed data set to examine whether credit risk of U.S. target firms differs when the buyer is either a U.S. domestic firm or a foreign country's firm. I assemble a comprehensive sample of acquired U.S. public firms by combining the weekly Markit dataset of CDS prices with the daily M&A transaction information from SDC Thomson, and then with each target firm's financial statement in COMPUSTAT. The CDS market provides a high-quality data source for the measurement of credit risk. At the same time, the CDS market offers several important advantages to study empirically whether foreign ownership relates to higher or lower corporate risk. Since CDSs are contracts and not securities in the traditional sense, the CDS market is more liquid than other markets, such as the relatively illiquid corporate debt market. While it can be sometimes difficult and costly to short corporate bonds and equities, it is easy to trade CDSs. Furthermore, CDSs provide a very easy way to assess credit risk since an increase in the CDS spread of a particular firm reflects an increase in the perceived risk of default by market participants. Thus, the market-based CDS data allows a timely measure of the change in risk as perceived by the market.

I apply a difference-in-differences approach to study the relation between credit risk and foreign block acquisitions. The results show that firm's ownership structure is relevant in explaining the variation in credit risk, over and above standard controls such as liquidity and credit rating. In particular, firms that are acquired by foreign investors exhibit on average a 42 basis points increase in their CDS premium (perceived credit risk goes up) after the acquisitions compared to firms which have been acquired by domestic investors. Over the subsequent 5 years, the CDS spread increases by 35 basis points in year five for the foreign-acquired firms relative to domestic-acquired firms and also relative to the year prior the acquisition. I also use stock return volatility as a measure of firm-level risk to test the impact of foreign block purchases on corporate risk. I find evidence that cross-border block acquisitions increase the total and the idiosyncratic risk component in the target firms stock volatility, probably due to the larger international exposure. Indeed, foreign-owned firms might face large international exposure since they might become less sensitive to local information and more sensitive to world events (Bekaert, Harvey, and Lumsdaine, 2002).

My findings provide evidence that foreign ownership has a positive impact on the credit risk of the target firm. The results are consistent with the argument that foreign investors are international diversified and benefit from international risk-sharing. Diversified capital ownership encourages firms to shift from low-return, safe investments toward high-return, risky investments (Obstfeld, 1994; Acemoglu and Zilibotti, 1997; Faccio, Marchica, and Mura, 2011). Another reason why foreign acquisitions might increase firm-level credit risk is related to the role of asymmetric information. The informational disadvantage of foreign investors is one of the main obstacles that prevent them to engage in active monitoring in foreign markets (Kang and Kim, 2008, 2010). One reason why domestic investors have an information advantage is that information does not have to travel over physical, linguistic, or cultural distances. Consistent with this view, I find a large increase in post-acquisition credit risk for the U.S firms that are acquired by foreign investors who are in a position of informational disadvantages by being either more geographically distant or more culturally different. This evidence supports the asymmetric information explanation whereby the reduced ability of foreign investors to monitor the managers exacerbates risk-shifting. Moeller, Schlingemann, and Stulz (2007) find that proxies for asymmetric information are helpful in predicting acquirer stock returns. When there is more asymmetric information, managers are better able to hide potentially value-decreasing activities from outside shareholders with more asymmetric information. One indication of asymmetric information is idiosyncratic equity volatility, higher values of which may make it easier for managers to hide risk increasing activities because they might simply be interpreted as reflecting a random outcome of greater ex-ante uncertainty (Dierkens et al., 1991). I also find a strong link between idiosyncratic volatility and foreign ownership, which introduces a channel for the positive relation between foreign acquisitions and credit risk. Moreover, the positive link between foreign acquisition and credit risk is consistent with a differences of opinion hypothesis. Indeed, foreign-acquired firms experience higher exposure to dispersion of analysts' earnings forecast, and in turn increase firm-level credit risk due to future cash flow uncertainty in corporate credit markets (Güntay and Hackbarth, 2010). Using a firm's specific index of diversity of opinion based on earnings forecasts from the Institutional Brokers Estimate System (I/B/E/S), I find a strong relation between foreign ownership and dispersion of analysts' earnings forecast, which provides further evidence on the increased uncertainty regarding the prospect of acquired firms.

I gain further insights on the relationship between foreign ownership and credit risk by developing a number of additional testable hypotheses that involve dividing my sample into various subgroups consisting of: (1) acquisitions from developed versus emerging markets, (2) majority versus minority control acquisitions, (3) firms not in the same industry as the acquiring firm, and (4) acquisitions financed solely by cash. When I partition the sample by acquirer characteristics, I find that credit risk positively and significantly changed after acquisition for both acquirers from developed and emerging markets. After I grouped the sample by deal characteristics, the post-acquisition ownership percentage and the deals in which the acquirer firm and the target firm are from different industries are the most striking driver of credit risk, exhibiting manifest differences between foreign and domestic acquisitions. These findings highlight how accounting for heterogeneity in acquirer types and deal characteristics reveal different channels by which post-acquisition credit risk is changed.

As a further check, I use a triple differences approach by including non-acquired CDS firms to my sample. This methodology allows us to capture the acquisition announcement effect. da Silva et al. (2015) provide evidence that CDS spreads increase with M&As announcements. I find that foreign-acquired firms experience a much higher increase in CDS price compared to the non-acquired firms. Together, these findings provide strong support for the claim that the creation of sizeable foreign ownership stakes is associated with a higher cost of default insurance.

The beauty of using market-based CDS data is that it reacts quickly to any changes affecting a firm credit risk. Although it is difficult for foreign acquirers to time the market perfectly, still a potential endogeneity problem might arise due to the selection of target firms. Thus, the empirical challenge in estimating the change in credit risk after the acquisition is one of causality versus selection. Are foreign investors simply picking certain types of acquisition targets or do foreign block acquisitions change target-firm credit risk? In an attempt to control for a such potential self-selection problem, I use a propensity score matching (PSM) analysis. Using a difference-in-differences combined with PSM, I find consistent results with the previous findings. That is, CDS spread for foreign-acquired firms increases significantly compared with the control (matched) group of non-acquired firms.

This paper makes a number of contributions to the literature. First, it contributes to the emerging and rapidly-growing literature concerning the role of foreign investors. A large body of literature has studied the role of foreign ownership on firm performance (see, e.g., Aitken and Harrison, 1999; Arnold and Javorcik, 2009; Chen, 2011; Chari et al., 2012). These studies have focused on the effects of foreign ownership on plant-level productivity measures such as total factor productivity (TFP), or labor productivity, or firm-level profitability measured as return on assets (ROA). The rationale in these studies is that if there are gains from foreign acquisitions they should be ultimately reflected in firms' performance. My contribution is to show that foreign investors also strongly influence another fundamental dimension of a firm which is its risk level. In addition, this paper contributes the cross-border acquisitions literature by investigating the response of the targets' credit risk to cross-border acquisitions announcements. The change in credit spreads has important implications for the wealth of existing shareholders and debtholders (Billett, King, and Mauer, 2004). Although debtholders do bear risk and take losses when the condition of firms deteriorate, they do not share the potential upside gains of risk-taking activities that only accrue to firm managers and stockholders. Moreover, this work adds to the growing empirical research on credit default swaps by showing that foreign-acquired firms have a higher credit risk premium as measured by their CDSs.

The remainder of the paper is structured as follows. Section 2 discusses how foreign ownership may influence firm-level credit risk and develop testable hypotheses. Section 3 provides a description of the data. Section 4 describes the methodology. Section 5 presents the empirical results. Section 6 provides evidence from the US equity market. Section 7 examines the economic channels, Section 8 provides further analyses and robustness checks, and Section 9 concludes.

## 3.2 Hypotheses Development

Foreign ownership plays a prominent role in firm-level risk, going back to micro-founded models of Obstfeld (1994), and Acemoglu and Zilibotti (1997), which focus on financial diversification. Both models introduce a trade-off between risk and productivity at the microeconomic level: firms must choose between safe low-productivity investments and risky high-productivity investments. Therefore, the desire to achieve better diversification pushes investments towards risky projects.

One of the main reasons why investors acquire foreign firms is related to international portfolio diversification and to benefit from international risk-sharing. Obstfeld (1994) shows that diversified capital ownership encourages firms to shift from low-return, safe investments toward high-return, risky investments. If investors buy shares in a firm for diversification purpose, we expect to find a positive relation between foreign ownership and firm-level risk. The reason is that foreign owners are likely to own properties in their domestic economy, and in turn have internationally diversified assets. This situation leads foreign investors to be better diversified against shocks to the domestic economy. As a result, they are more tolerant to domestic risk and more likely to tilt investment towards risky projects (Obstfeld, 1994). Thus, diversification opportunities are more prominent among foreign owners due to their internationally diversified portfolios. Such international diversification motivates foreign owners to push managers to undertake riskier projects so as to create shareholder value (Faccio et al., 2011). To create shareholder value, firms invest in projects that are associated with high level idiosyncratic risk.

Informational asymmetry in the equity and credit markets is also a crucial channel that could justify an impact of foreign ownership on firm-level risk. The informational disadvantage of foreign investors is one of the main reasons for their reluctance to invest in foreign markets (see, e.g., Kang et al., 1997; Brennan and Cao, 1997). One reason why domestic investors have an information advantage is that information does not have to travel over physical, linguistic, or cultural distances. Dvořák (2005) finds that domestic investors have higher profits than foreign investors and domestic clients of global brokerages have higher profits than foreign clients of global brokerages by using transaction data from Indonesia. Chan et al. (2008) also show that foreign investors face more severe information asymmetry compared to domestic investors. For these reasons, foreign investors may be less effective monitors. Indeed, the presence of asymmetric information due to unfamiliarity with the foreign markets increase agency problems and difficulties in effectively monitoring managers abroad. Issues such as the decreased ability of shareholders to monitor managers, information asymmetry between local firms and foreign acquirer, and increased managerial risk-taking activities are likely to increase the riskiness of target firms (Reeb et al., 1998; Kim and Mathur, 2008). Moeller et al. (2007) find that proxies for asymmetric information are helpful in predicting firm stock returns. More asymmetric information implies that managers are better able to hide potentially value-decreasing and risk-increasing activities from outside shareholders. One indication of asymmetric information is a high value of idiosyncratic stock volatility, which may make it easier for managers to hide risk increasing actions since they might simply be interpreted as reflecting a random outcome of greater ex-ante uncertainty (Dierkens et al., 1991).

The CDS market is a bilateral dealership over-the-counter market, with no centralized quote disclosure mechanism and with a less than fully competitive network of private dealers, usually controlled by a group of major banks (Augustin et al., 2014). Therefore, a significant portion of trading in the CDS market occurs among large financial intermediaries who are sophisticated investors. Acharya and Johnson (2007) argue that some of the dealers in the CDS market are potentially informed about companies' private credit information because of their exposure to the loan market. Thus, the market might react differently to foreign takeover announcements relative to domestic takeovers.

From the preceding discussions, it can be concluded that foreign ownership plays a vital role in target firms risk. As foreign capital becomes an increasingly important source of financing around the world (Bekaert et al., 2002), it is essential to investigate the effects of foreign block acquisitions on firm-level credit risk. The first hypothesis to be tested is:

**H1.** Foreign block purchases are positively and significantly associated with target firms' credit risk.

I explore cross-sectional differences in the extent to which the impacts of foreign ownership on the target firms' credit risk are related to acquirer and transaction characteristics. The first dimension I consider is the country of origion of the acquirer. Consistent with the predictions of the Helpman et al. (2004) model, Chen (2011) find that target firms are subject to significantly different restructuring processes depending on the origin of the acquiring firm. Therefore, acquisitions from developed markets might have a different impact than of emerging markets on the targets' credit risk. I partition the sample by acquirer characteristics to proceed with the analysis of whether the country of origin of the acquirer matters. More formally:

**H2.** The positive impact of foreign block acquisitions on target firms' credit risk differs with developed or emerging market acquirers.

The effect of foreign investors on the target firm's policy may also vary with cross-sectional heterogeneity in the acquired stakes. Cronqvist and Fahlenbrach (2009) find that large shareholders play an important role in corporate policy choices and firm performance. Chari et al. (2009) find that the percentage of post-acquisition ownership emerged as one of the most impactful transaction characteristics on the premium paid to targets shareholder wealth in cross-border acquisitions. Moreover, a large ownership by a foreign investor might exacerbate agency problem due to asymmetric information and difficulties in monitoring manager abroad. Thus, in a target firm with a concentrated foreign ownership, managers are more able to mask his activities from outside shareholders and take risk-increasing activities. To capture these differences, I divide my sample of acquired firms into two subgroups consisting of majority and minority control acquisitions. I define a minority block acquisition as the one in which the acquirer purchases more than 5% and less than 50% of the target's stake. A majority block acquisition is the one in which the acquirer purchases more than 50% of the target's stake, in turn, there is a change in control. Cross-sectional heterogeneity in the block size yield additional predictions on the effect of foreign purchases on targets' credit risk. More formally:

**H3.** The positive association between foreign block purchases and credit risk is stronger (weaker) with majority acquisitions (minority acquisitions).

Finally, previous studies have shown that the method of payment and degree of diversification are transaction characteristics that play a significant role in acquisitions' successful completion and wealth effects. A diversifying acquisition may have negative effects on the target's value. It may intensify agency problems, allow poor segments to drain resources from better performing segments, and misalign incentives of central and divisional managers, all of which may have value-reducing effects and thereby might increase credit risk (see, e.g., Stulz, 1990; Berger and Ofek, 1995; Laeven and Levine, 2007). Alternatively, using cash as a means of exchange is likely to increase the liquidity of the acquired firm, which in turn might decrease its credit risk (Billett et al., 2010). Announcement returns of cash deals are consistently found to be higher than those of stock deals, both for the acquirer and the targets (Andrade et al., 2001). This discussion suggests testing the following hypotheses:

**H4.** The positive impact of foreign block acquisitions on target firms' credit risk is more pronounced with diversifying deals.

**H5.** The positive impact of foreign block acquisitions on target firms' credit risk is less pronounced with deals financed solely by cash.

## 3.3 Data Description

The dataset is a result of a merge of five data sources: Thomson Financial database for block acquisitions, Markit for CDSs, Center for Research in Securities Prices (CRSP) for stock volatility, Institutional Brokers Estimate System (I/B/E/S) database for analyst earnings forecasts, and COMPUSTAT North America for firm balance sheet. The merged data set contains weekly information on 863 completed block acquisitions (180 foreign and 683 domestic) over the period 2001-2014.[3]

### 3.3.1 Block Acquisitions Data

The Thomson Financial data sample contains deals involving at least 5 percent acquisitions of public U.S. target companies that were announced and completed between January 1, 1980, and December 31, 2014, and are reported by SDC Platinum. I focus on publicly traded U.S. targets since open financial markets in the U.S. have led to a substantial number of cross-border block acquisitions and public U.S. firms are required to disclose detailed accounting data. Similar to Erel, Liao, and Weisbach (2012), I exclude leveraged buyouts, spin-offs, recapitalizations, self-tender offers, exchange offers, repurchases, acquisitions of remaining interest, privatizations, buybacks, and non-controlling acquisitions. For each transaction, the SDC database provides information about the date on which the transaction was announced and the date on which the transaction became effective or was withdrawn. The database also provides information about some characteristics of the target and acquiring firms such as name, nation, industry sector, North American Industry Classification System (NAICS) code. For each transaction, SDC also reports the percentage of shares acquired before and after the transaction is completed, the value of the transaction, the number of bidders, the method of payment, and whether the target firm is delisted as a result of an acquisition. The sample includes only those target firms that are kept as independent units

[3]Note that I collect the acquisition data starting from 1980 to control for firms which have been acquired by foreign investors over the period 1980-2000.

and whose financial data are publicly available after acquisitions.

Information provided in SDC on the target firms allows matching across these databases. During this process, I lose observations because some of the target firms are renamed after the acquisition or are delisted. In addition, there are target firms that have been acquired more than once by both U.S. acquirers and foreign firms. I only include the first of multiple acquisitions in my data set since the paper is interested in what happens to a U.S. target firm's credit risk when it is first acquired by a foreign market firm. Moreover, I eliminate firms from countries that are considered tax havens, such as Bahamas, Bermudas.[4] The matched dataset is limited to firms with publicly traded bond issues that have CDS contracts written on their debt securities.

Table 3.1 presents information by country of origin on the number and value of acquisitions of U.S. firms. The top five foreign countries whose firms acquired U.S. targets over the period 1980-2014 are: Canada, United Kingdom, Japan, France, and Germany.

Figure 3.1 shows the total value in millions of USD of cross-border transactions into the United States by emerging and developed market firms over the period 1980-2014. The investment outlays into the United States made by emerging market firms indicates a small surge in 2000, and a more pronounced surge in the latter half of the decade beginning in 2004. However, we observe a decline in acquisitions by emerging markets after the 2007-2009 financial crisis. On the other hand, we note a dramatic increase in developed market cross-border acquisitions during 1997-2001, 2004-2009, and after 2013.

### 3.3.2 CDS Data

In order to measure firm-level credit risk, I use CDS quotes from Markit, which has become the standard source for academic research.[5] A CDS contract represents insurance

[4]List of tax-haven countries (as defined by the OECD, 2008) excluded from the sample: Bahamas, Bermuda, British Virgin Islands (United Kingdom), Cayman Islands, Cook Islands, Cyprus, Isle of Man, Jersey, Liechtenstein, Marshall Islands, Mauritius, Netherlands Antilles, Panama, US Virgin Islands (United States).

[5]Markit obtains contributed CDS data from market makers' official books and records, which undergo rigorous data cleaning to guarantee that only the highest quality data is used in forming composite quotes. I use the five-year CDS spreads since they are the most liquid contracts and form over 85% of the whole CDS market (Jorion and Zhang, 2007).

against the default of an entity. The payment of a CDS contract represents the CDS premium and is stated as a percentage of the value of the contract. Thus, CDS spreads provide a direct measure of the credit risk for the underlying entity. In addition, recent empirical evidence asserts that CDS spreads are an effective and more timely measure of credit risk of an entity compared to the bond or stock market indicators (see, e.g., Jorion and Zhang, 2007; Blanco et al., 2005; Zhu, 2006).

The weekly CDS data set ranges from January 2001 to April 2014. I use weekly spreads for five-year, USD-denominated, senior tier CDS contracts with the modified restructuring (MR) clause, as those type of contracts are the largest and most liquid.[6] All CDS prices are winsorized at the 1$^{st}$ and 99$^{th}$ percentile. In addition to CDS quotes, Markit also provides information about sector, country and region classifications for the underlying firms. Since the goal of the paper is to analyze the effect of the ownership structure on CDS premium in the U.S, differences in sector within the empirical analysis will be controlled by using analogous fixed effects.[7]

### 3.3.3 Stock Return Volatility Data

Stock return volatility serves as a dependent variable in the regressions for stock returns volatility, and as a control variable in the regressions for CDS spreads. The data is from the CRSP database over the period 1980-2014.

### 3.3.4 Differences of Opinion Index

To obtain a proxy for diversity of opinion, I use analyst forecasts of earnings per share, from the Institutional Brokers Estimate System (I/B/E/S) database over the period 2001-2014. This database contains individual analyst's forecasts organized by forecast date and the last date the forecast was revised and confirmed as accurate. The dataset also contains forecast

[6] For more information about the documentation clauses, see ISDA Credit Derivatives Definitions published in February 2003.
[7] I also run robustness check by excluding firms in financial sector.

horizons of one, two and three years ahead and long-run forecasts. I use only one-year-ahead forecasts on EPS to avoid losing too many observations and to ensure the highest explanatory power. To circumvent the problem of using stock-split adjusted data, I use unadjusted data. I extend each forecast date to its revision date. If an analyst makes more than one forecast per month, I take the last forecast that was confirmed.

### 3.3.5 Geographic Distance and Cultural Difference Data

I use geographic distance and cultural differences as proxies for asymmetric information. To calculate the Great Circle Distance between foreign acquirer and the US targets, I obtain the latitude and longitude of capital cities of each foreign country from mapsofworld.com.[8] I acquire data on national culture from Hofstede's website.

### 3.3.6 Control Variables

A large amount of empirical literature has studied the potential determining factors of CDS spreads, and stock return volatility. This literature has suggested several economic variables having explanatory power for CDS spreads, or stock return volatility. To focus on the additional explanatory power of foreign acquisitions, I include in the regressions several of these variables as controls. A first obvious control variable in all the regressions is firm leverage, which is defined as total debt divided by total assets. In the regression for CDS spreads, I additionally control for firm size, defined as the log total book value of assets and for firm profitability (ROA), defined as operating income before depreciation, amortization and taxes (OIBD) divided by total assets. Leverage, firm size, and ROA data are retrieved from the COMPUSTAT North America database.

In the regressions for CDS spreads, I additionally control for market liquidity and stock return volatility. Markit reports CDS depth, the number of dealers that contributed to the

[8]The standard formula to calculate great circle distance is: $3963.0 * arcos[sin(lat1) * sin(lat2) + cos(lat1) * cos(lat2) * cos(lon2 - lon1)]$, where lon and lat are the longitudes and latitudes of the acquirer and the target country locations, respectively.

quote formation, which I use as a CDS-level proxy for liquidity following Qiu and Yu (2012). In addition, the Merton (1974) model predicts that the credit spread is linked to stock return volatility. Appendix A provides a detailed description of the variables used in this study.

Table 3.2 reports summary statistics for my main variables of interest. My final sample consists of 863 completed block acquisitions, of which 180 are made by foreign firms. Panel A presents the descriptive statistics for the entire sample, whereas Panel B and C presents summary statistics for foreign-acquired and domestically acquired target firms separately. Target firms acquired by foreign firms exhibit higher CDS spreads and stock volatility relative to domestic acquisitions. Hence, below I employ a formal regression framework.

## 3.4 Methodology

To test for the impact of foreign ownership on credit risk, I rely on the following difference-in-differences methodology:

$$ln(CDS_{i,t}) = \alpha_i + \alpha_t + \beta Post_{i,t} * Foreign_{i,t} + \theta X_{i,t} + \epsilon_{i,t} \tag{3.1}$$

The dependent variable, $ln(CDS_{i,t})$, is the natural logarithm of CDS premium for firm $i$ in week $t$. As in Bai and Wu (2015) all regressions are on the logarithms of CDS for better distributional behaviors. The variable $Post_{i,t}$ denotes a dummy variable for the second (post acquisition) time period. $Foreign_{i,t}$ equals one for foreign-acquired firms (treatment group), and zero for domestic-acquired firms (control group). In the analysis, $X_{i,t}$ denotes a vector of control variables for firm (size, leverage, profitability, volatility of assets) and market characteristics (market depth as a proxy for liquidity, and recovery rate). Moreover, $\alpha_i$ and $\alpha_t$ are firm and time fixed effects respectively. I use firm fixed effects to control for unobservable and time-invariant firm heterogeneity (such as location, or industry). I also use time fixed effects (i.e. year dummies) to capture omitted time variant effects. $Post_{i,t}$ and $Foreign_{i,t}$ drop out of the regression due to the firm fixed effects and time fixed effects.

Results are consistent when one use $Post_{i,t}$ and $Foreign_{i,t}$ dummies instead of time and firm fixed effects. Furthermore, standard errors are clustered at the firm level to capture the unspecified correlation between observations on the same firm in different years. The variable of interest is the interaction, $Post_{i,t} * Foreign_{i,t}$, a dummy variable equal to one if a firm is acquired by foreign investors and if the time involves post-acquisition period, and zero otherwise.

I also run the difference-in-differences regressions over 1-5 year window following the acquisitions. More specifically, for the weeks in the year of acquisition, I set $t = 0$, for the weeks in the years following the acquisition $t = 1, ..., 5$, and for the weeks in the year prior to the acquisition, $t = -1$, etc. The variables of interest are the interaction variables for each of the five years following the acquisitions.

Moreover, I run the difference-in-differences regressions by dividing my sample into various subgroups consisting of: (1) acquisitions from developed versus emerging markets, (2) majority versus minority control acquisitions, (3) firms not in the same industry as the acquiring firm, and (4) acquisitions financed solely by cash.

## 3.5 Empirical results

In this section, I provide the main results for the impact of foreign ownership on CDS spreads. I also provide evidence based on time-series and cross-sectional analyses.

### 3.5.1 Foreign acquisitions and credit risk

To gauge first insights into the association of CDS spreads and foreign acquisition, I examine their cross-sectional relation over time. In Figure 3.2, I chart the average CDS premium in log and basis points (in parenthesis) for the treatment and the control group over the weekly time series. The solid line represents the treatment group (CDS price of foreign-acquired firms) while the dashed line shows the control group (CDS price of domestic-acquired firms). The goal of the graph is to visually show that the post-event relationship between variables is not a continuation of their pre-event trends. 3.2 suggests that foreign-acquired firms experience a higher increase in their CDS spreads which is not the continuation of a time-trend. At the first glance, the impact of foreign ownership on CDS premium appears as causal.

Table 3.3 reports the estimates for equation (1). Column (1) contains the results when pooling all foreign block acquisitions. Consistent with hypothesis H1, the results show that the interaction coefficient is about 0.34 in terms of log and statistically significant when controlling for a full range of controls and other relevant fixed effects.[9] The economic magnitude of the interaction coefficient is about 42 basis points. Thus, foreign-acquired firms experience a 42 basis points increase in their credit risk following the acquisition compared to domestic-acquired firms.[10]

Note that the key identifying assumption behind difference-in-differences strategy is that, in the absence of treatment, the observed difference-in-difference estimator is zero. This assumption is similar to parallel trends assumption since it requires that the trend in the outcome variable for both treatment and control groups during the pre-treatment era are similar. However, this assumption does not require that the level of outcome variables to be identical across the two groups or the two eras. I perform a t-test of the difference in average outcome variables growth rates across the treatment and control groups during the pre-treatment era. The parallel trend assumption holds in the current setting as I find that the t-stat is equal to 0.1336 which turn out insignificant. Although there are divergent trends in CDS levels before the treatment in Figure 3.2 most probably due to potential leakage of information about the deal and announcement effects, it passes the test.

Next, I examine whether the positive effect of the foreign acquisitions on the target's credit risk arises due to acquirer characteristics. In column (2) and (3), I split between acquisitions

[9] All regressions are on the logarithms of CDS for better distributional behaviors.

[10] I find consistent results (not reported) when I use percentage changes in CDS premium, $(CDS_{i,t}/CDS_{i,t-1} - 1)$, as a dependent variable.

by developed countries firms and by emerging markets. Consistent with hypothesis H2, the interaction coefficients are positive and statistically significant with different magnitudes. Targets acquired by developed markets tend to experience in log a 0.37 (45 basis points) increase in their credit risk following the acquisition relative to domestic-acquired firms. In addition, targets acquired by emerging markets experience in log a 0.28 (33 basis points) increase in their credit risk following the acquisition compared to domestic-acquired firms. Overall, these findings reveal that foreign block acquisition has significant implications for the credit risk of the target firms.[11]

### 3.5.2 Foreign acquisitions and credit risk over 1-5 year window

I also analyze the post-acquisition CDS spreads reaction to foreign block acquisitions over 1-5 year window. Note that the changes in post-acquisition CDS spreads are calculated relative to year $t = -1$, prior to the acquisition, with $t = 1, ..., 5$ denotes the post-acquisition years.

The results in Table 3.4 show that CDS spread start to increases in years 1-5 following a foreign acquisition and the increase is statistically significant. In particular, the log CDS premium significantly increases in log by 0.30 (35 basis points) over five-year window for the foreign-acquired firms relative to the domestic-acquired firms and also relative to the year prior to the acquisition.[12] These findings indicate that I uncover robust and significant relation between foreign ownership and credit risk at firm-level.

### 3.5.3 Transaction characteristics

It is natural to ask whether the association between foreign acquisition and CDS spreads depends on acquirer and transaction characteristics.

Table 3.5 reports the estimates for subgroups consisting of: (1) majority and minority

[11] These results also hold when I exclude financial firms from my sample.

[12] The results from using the lagged values of control variables are also consistent with these findings. The relative increase in credit risk of foreign-owned firms appears to persist across the five years following the acquisition.

control acquisitions, (2) firms not in the same industry as the acquiring firm (diversifying) and horizontal deals, lastly, (4) acquisitions financed solely by cash. Consistent with hypothesis H3, the results indicate that post-acquisition CDS spread changes in the 51-100 percent ownership (majority controls) category are much larger than those of the 5-50 percent ownership (minority controls) group: the interaction coefficient in log is about 0.32 (39 basis points) and statistically significant vs. 0.15 (18 basis points) and insignificant. In addition, consistent with hypothesis H4, post-acquisition CDS spread changes in the firms not in the same industry as the acquiring firm (diversifying deals) are much larger than those of the firms in the same industry (horizontal deals) group: the interaction coefficient in log is about 0.34 (42 basis points) and statistically significant vs. 0.10 (11 basis points) and insignificant. Additionally, the method of payment is characterized as either cash, which represents all-cash acquisitions, or stock or mixed. Based on this classification, I find evidence that cash deals increase targets' credit risk, but the coefficient is not statistically significant which is consistent with hypothesis H5. Note that, the statistical significance of the results varies because of sample sizes. For example, for the group of horizontal acquisitions, in which both acquiring and target firms share the same industry, the sample size is much smaller than that for diversifying acquisitions. Thus, the magnitudes of the estimates and statistical significance different for some subgroups to those of the whole sample.

I also use nested models (e.g., $Post_{i,t} * Foreign_{i,t} * Stake_{i,t}$) to assess the differences in subgroups. Table 3.6 shows that only differences between majority and minority acquisitions is statistically significant.[13]

In summary, the findings suggest the following: Compared to U.S. domestic block acquisitions, foreign-acquired firms experience a higher CDS premium (perceived credit risk goes up) after the acquisitions. Thus, foreign ownership plays a key role in a company's credit risk.

[13] Note that other interaction terms ($Post_{i,t} * Stake_{i,t}$ and $Foreign_{i,t} * Stake_{i,t}$) drop out of the regression due to the firm fixed effects and time fixed effects.

## 3.6 Foreign Acquisition and Stock Volatility

In this section, I investigate the impact of foreign block acquisition on stock-level volatility. In order to evaluate the effects of foreign block acquisitions on U.S. target firms' risk, I examine stock market performance, measured as firm-level stock volatility over the period 1980-2014.[14] Harris and Ravenscraft (1991) examine the effects of inbound U.S. FDI on shareholder wealth over the period 1970-1987 and find that target firm's wealth gains are significantly higher in cross-border takeovers than in domestic acquisitions. To test a relation in which foreign ownership leads to an increase in corporate risk, I provide evidence from the U.S. equity market.

In addition to the difference-in-differences (DD), I also use a triple differences (DDD) approaches by including non-acquired U.S. firms to my sample in order to capture M&As announcement effects. The DD and DDD approaches take the following forms, respectively:

$$Volatility_{i,t} = \alpha_i + \alpha_t + \beta Post_{i,t} * Foreign_{i,t} + \theta X_{i,t-1} + \epsilon_{i,t} \tag{3.2}$$

$$Volatility_{i,t} = \alpha_i + \alpha_t + \beta Post_{i,t} * Treated_{i,t} * Foreign_{i,t} + \theta X_{i,t-1} + \epsilon_{i,t} \tag{3.3}$$

The sample frequency is quarterly, and the dependent variable is the stock's daily return volatility measured over the calendar quarter. Note that in equation (3), I include an additional term, $Treated_{i,t}$, which is an indicator variable that equals one for firms in the treatment group (both domestic and foreign acquired firms) and zero for firms in the control group (non-acquired firms)

Following Ben-David et al. (2016), I include the following controls: lagged log(market cap), lagged book-to-market ratio, past 6-month returns, lagged inverse price ratio ($1/price$), and lagged Amihud illiquidity measure (Amihud, 2002). In addition, my specifications include firm and calendar quarter fixed effects. Standard errors are clustered at the firm level throughout this analyses. The variable of interest, the interaction between $Post_{i,q}$

[14] The results are robust to including only firms that have CDS traded on their debt securities.

and $Foreign_{i,q}$, captures the impact on volatility of foreign block purchases following the acquisition relative to the pre-acquisition effect of the domestic acquisition.

The basic methodology I use in this section is to compare the firm-level risk measures of the target firms before and after the acquisitions. I define firm-level risk as the stock return volatility (total risk) and then I decompose it in its systematic and idiosyncratic components. To measure total risk, I compute the standard deviation of the stock returns based on the daily stock returns for each target firm. I decompose the total risk by using the capital asset pricing model (CAPM) or Fama-French three-factor (FF3F) model by regressing the daily stock returns of each target firm in the sample on the corresponding market index return or Fama-French three factors.

Figure 3.3 presents the average stock volatility of the treatment and control group over the event window. The solid line represents the treatment group (stock volatility of foreign-acquired firms) while the dashed line shows the control group (stock volatility of domestic-acquired firms). The goal is to visually show that the post-event relationships between variables are not a continuation of their pre-event trends. Figure 3.3 shows that foreign-acquired firms experience a higher increase in their stock volatility which is not the continuation of a time-trend. At the first glance, the impact of foreign ownership on stock volatility is causal.

Table 3.7 reports the DD estimates. The results show that compared to the domestic block acquisitions, foreign block acquisitions are associated with a higher volatility (Vol) and its unsystematic risk component (Idio_vol_m, or Idio_vol_f) following the acquisition. The coefficient on the interaction in Column (1) shows that compared to U.S. domestic acquisitions, acquirers from foreign markets lead to about 20 basis points increase in the daily volatility of stock following the acquisition. The coefficients on the interaction in Column (3) and in Column (4) indicate that compared to U.S. domestic-acquired firms, foreign-acquired firms experience about 20 basis points increase in the unsystematic component of the daily volatility of stock following the acquisition.

Table 3.8 reports DDD estimates and the results are consistent with DD estimates.[15] The association between idiosyncratic risk and foreign ownership is positive and statistically significant. Note that these findings are reasonable since we can expect that the foreign-acquired firms might have more financial exposure to the foreign markets and less dependence on the local financial market following the acquisitions (Bekaert et al., 2002). The results in Table 3.8 Column 2 also document a negative association between foreign block acquisitions and systematic risk. The reason is that international diversification reduces variability in the firm's earnings resulting from less than perfect correlation between earnings in different markets (Agmon and Lessard, 1977). Indeed, one of the main reasons why investors acquire foreign firms is to realize diversification benefits which create shareholder value. These benefits arise from international risk-sharing and reduced degree of systematic risk.

In summary, the results suggest that compared to the domestic block acquisitions, foreign block acquisitions increase the total risk and the unsystematic risk of the target firms due to increased international exposure. The results also suggest that foreign acquisitions decrease systematic risk owing to diversification benefits.

## 3.7 Why foreign acquisitions increase credit risk

In this section, I discuss why foreign acquisitions add credit risk, and provide empirical support for the channels that explain the positive relation between foreign purchases and credit risk.

### 3.7.1 Idiosyncratic volatility and asymmetric information

Foreign investors generally face more information asymmetry with the managers compared with domestic investors (see, e.g., Brennan and Cao, 1997; Hau, 2001; Chan et al., 2008). As a result, they may be less effective monitors. Indeed, the presence of asymmetric information

[15] Note that other interaction terms ($Post_{i,t} * Foreign_{i,t}$ and $Foreign_{i,t} * Treated_{i,t}$) drop out of the regression due to the firm fixed effects and time fixed effects.

due to unfamiliarity with the foreign markets increase agency problems and difficulties in effectively monitoring managers abroad. Issues such as the decreased ability of shareholders to monitor managers and increased managerial risk-taking activities are likely to increase the riskiness of target firms (see, e.g., Reeb et al., 1998; Kim and Mathur, 2008).[16] One indication of asymmetric information between management and shareholders is a high value of idiosyncratic stock volatility, which may make it easier for managers to hide risk increasing actions since they might simply be interpreted as reflecting a random outcome of greater ex-ante uncertainty (Dierkens et al., 1991; Moeller et al., 2007).

As the results in Table 3.7 and 3.8 indicate, foreign acquisitions have a positive and significant impact on the target firm's idiosyncratic volatility. The high level of idiosyncratic risk of a foreign-acquired firm after the acquisition is a sign for the market that managers of target firms are more able to hide risk increasing activities from outside shareholders. The findings are consistent with asymmetric information hypothesis that managers take advantage of the volatility of their stock prices. Thus, an exposure to high-level idiosyncratic risk creates a channel for the positive relation between credit risk and foreign acquisitions. Indeed, the results in Columns 2-5 of Table 3.9 show a positive and significant relationship between credit risk and idiosyncratic volatility.

### 3.7.2 Geographic distance and cultural difference

Several factors are likely to cause foreign investors to be less informed about a host country than domestic investors, and in turn to affect foreign investors' incentives to engage in active monitoring. One such factor is the physical distance between the foreign acquirer and the target firms. Several studies show that, in the US, investors located near a firm have an information advantage over other investors regarding to the firm, probably due to relatively easier access to value-relevant information about the firm (see, e.g., Baik et al., 2010; Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005; Kang and Kim, 2008). For

[16] In Subsection 7.2, I discuss more on the informational disadvantages of foreign investors and provide evidence between the proxies of asymmetric information and credit risk.

instance, Kang and Kim (2008) find that information advantage that arises from geographic proximity is an important determinant of domestic block acquirers' governance activities in the targets. Indeed, acquirers located near the targets can more easily obtain valuable private information about the targets through informal talks with CEOs and employees, or can more readily visit the targets, they have better access to information than do remote acquirers. Thus, the information advantages of geographically proximate acquirers provide them enhanced capabilities and stronger incentives to monitor their proximate targets. In addition, investors' monitoring costs increase with physical distance from the target because of extra communication and transportation costs (Petersen and Rajan, 2002). The difficulties in monitoring arising from the geographic distance make it harder for board and internal control systems to prevent sub-optimal decisions by managers. Thus, we might expect that foreign acquired firms would have higher information asymmetry problems and exhibit a higher credit risk, compared to domestic-acquired firms. Following Erel et al. (2012), I calculate the distance between capital cities of the foreign acquirer and US targets from mapsofworld.com as a proxy for geographic distance.

Second, cultural differences might be another important source of information asymmetry since it can make it more difficult and expensive for a foreign acquirer to obtain accurate information about the US targets. Kang and Kim (2010) find that foreign acquirers who do not have a similar culture as the US are less likely to involve in governance activities in the US targets. To measure cultural difference, I use Kogut and Singh (1988)'s index of national cultural distances, which is based on the differences in scores along each of Hofstede (1984)'s four cultural dimensions (power distance, uncertainty avoidance, masculinity, and individualism) between the host country and the foreign investor's home country.

Table 3.10 provides evidence on the link between foreign investors' informational disadvantages and post-acquisition credit risk using geographic distance and cultural differences as proxies of information asymmetry. In Column (1), I use the physical distance between the acquirers and their targets as a proxy for the measure of acquirer information asymmetry.

I find that post-acquisition CDS spread is positively related to the logarithm of physical distance between the acquirer and the target firms. This finding suggests that distance between acquirer and target is an important determinant of the increase in the target firms' post-acquisition credit risk. The result is consistent with that of Kang and Kim (2008), who show that geographically proximate block acquirers in the US are more likely to engage in post-acquisition governance activities in targets than remote acquirers. In Column (2), I use the cultural differences between the foreign acquirer's home country and the US as a proxy for informational disadvantages of foreign investors. The coefficient on cultural difference is positive and significant, suggesting that foreign acquirers that have a cultural distance with the US are associated with a high increase in the targets firms' post-acquisition credit risk.

In short, I find that post-acquisition CDS spreads increase for the U.S firms that are acquired by foreign investors who are in a position of informational disadvantages by being either more geographically distant or more culturally different. This evidence supports an asymmetric information explanation whereby the reduced ability of investors to monitor the managers exacerbates risk-shifting.

### 3.7.3 Diversity of opinion

Recent literature uses the dispersion of analyst forecasts as a measure of differences of opinion and establishes a positive relation between bond credit spreads and dispersion of analysts earnings forecasts (see, e.g., Buraschi et al., 2013; Güntay and Hackbarth, 2010). Buraschi et al. (2013)'s model predicts that higher heterogeneity of beliefs about consumption growth increases the market price of default and, consequently, bond risk premia and credit spreads. Empirically, they construct an aggregate measure of disagreement in earnings forecasts and report its positive association with firm-level credit spreads. They find that firms with higher exposure to common disagreement shocks unambiguously have larger bond returns and credit spreads. For instance, the quintile of bonds with the largest exposure implies an average credit spread that is 32 basis points larger than the average credit spread of the quintile of bonds with the lowest exposure. In addition, Güntay and Hackbarth (2010) focus on non-financial firms in the US from 1987 to 1998 and empirically document a positive relation between credit spreads and firm-specific measures of dispersion in earnings forecasts. More specifically, they find evidence that bonds of firms with higher dispersion demand significantly higher credit spreads than otherwise similar bonds and that changes in dispersion reliably predict changes in credit spreads. Consistent with a rational explanation, the authors argue that dispersion appears to proxy largely for future cash flow uncertainty in corporate bond markets.

Consistent with these views, using earning forecast data from the Institutional Brokers Estimate System (I/B/E/S), Figure 3.4 shows that foreign-acquired firms (solid line) experience higher exposure to dispersion in analysts' earnings forecasts compared to domestic-acquired firms (dashed line) after the acquisition. When I regress CDS spreads on the proxy for differences of opinion (see Column 1 in Table 3.9), I find a positive and significant relation between credit spreads and firm-specific measures of dispersion in analyst forecasts, consistent with the findings in Güntay and Hackbarth (2010), and Buraschi et al. (2013). This finding provides further evidence on the increased uncertainty regarding the prospect of acquired firms and introduces an alternative explanation for the positive link between CDS spreads and foreign ownership.

### 3.7.4 Shift in capital structure and risk transfer

I also examine two possible alternative reasons that might explain why foreign acquisitions increase credit risk. One potential reason might be that foreign acquirers tend to change target firm's corporate policies after the acquisitions (see, e.g., Harris and Ravenscraft, 1991; Chen, 2011; Chari et al., 2012). To examine this hypothesis, I test how target firms' investment, cash holdings, and financial leverage change after a foreign acquisition. I find that foreign ownership has a positive effect on the changes in investment, cash holdings, and leverage.

However, the results are neither statistically nor economically significant.[17]

A second potential reason for the increase in target default risk after an acquisition may be the transfer of risk from the acquirer. It might be that the typical foreign acquisition is risk-increasing from the target's point of view because the typical acquirer has more default risk than the typical target. Indeed, there is evidence of risk transfer in the response of bond prices to acquisition announcements. The bonds of target firms tend to increase in value if and only if the acquiring firm's bonds are higher rated, consistent with risk transfer to target bondholders (Billett et al., 2004). For the 80 acquisitions for which I have CDS data for the foreign acquirers, I find that foreign acquirers' CDS spreads also increase after the acquisitions.[18] This evidence suggests that the increase in targets' credit risk after a foreign acquisition is unlikely to come from risk transfer.

In the end, these findings suggests that the increase in credit risk after a foreign acquisition is best explained by idiosyncratic volatility, asymmetric information, and diversity of opinion.

## 3.8 Further Analyses and Robustness checks

The results based on the difference-in-differences estimation do not take into account the possibility that credit risk differences might arise due to the acquisition itself or the selection of target firm rather than the change in ownership. To rule out for these possibilities, I use a triple differences (DDD) approach and a propensity score matching analysis as robustness checks. Moreover, I conduct additional analyses to investigate the relationship between foreign ownership and CDS spreads by using data on multiple and failed transactions.

### 3.8.1 A Difference-in-Difference-in-Differences Approach

A potential concern with the previous analysis is that other factors unrelated to ownership change might affect the credit risk of a foreign-acquired firm relative to a domestic-acquired

[17] Results are available upon request from the author.
[18] Results are available upon request from the author.

firm, such as M&As announcements. In other words, acquisition itself regardless of being foreign or domestic might change credit risk of an acquired firm compared to a non-acquired firm. For instance, da Silva et al. (2015) find that, on average, CDS spreads increase with acquisition announcements. To capture the acquisition announcement effect, I estimate a DDD specification that compares difference across the two groups for targets involving foreign-acquired versus domestic ones before and after the event dates and then compares the credit risk of firms within the treatment (acquired firms) and control groups (non-acquired firms).

The DDD is performed using the following estimation equation:

$$ln(CDS_{i,t}) = \alpha_i + \alpha_t + \beta Post_{i,t} * Treated_{i,t} * Foreign_{i,t} + \theta X_{i,t} + \epsilon_{i,t} \tag{3.4}$$

where $Post_{i,t}$ is an indicator variable that equals one for all the years after the acquisition date and zero otherwise; $Treated_{i,t}$ is an indicator variable that equals one for firms in the treatment group (both domestic and foreign acquired firms) and zero for firms in the control group (non-acquired firms); and $Foreign_{i,t}$ is an indicator variable that equals one for foreign-acquired firms and is zero for the domestic-acquired ones. All regressions are estimated with firm ($\alpha_i$) and time ($\alpha_i$) fixed effects. Note that, this specification allows us to assess the change in credit risk of firms when the targets in the treatment group are acquired by foreign investors, relative to the firms in the control group (non-acquired firms) ($\beta$).

Table 3.11 reports estimates for equation (4). The results in Table 3.11 are consistent with the results in Table 3.3. As can be observed from both tables the coefficient of interaction, $\beta > 0$, suggesting that firms that are acquired by foreign investors experience a higher increase in their credit risk after the acquisition, relative to firms in the control sample (non-acquired firms). In particular, firms that are acquired by foreign investors exhibit about 0.25 (28 basis points) a higher CDS premium after the acquisitions compared to non-acquired firms. This finding provides strong support for the claim that the creation of sizeable foreign ownership stakes is associated with a higher cost of default insurance.

### 3.8.2 Propensity Score Matching Approach

The results based on the difference-in-differences estimation do not take into account the possibility that credit risk differences may arise due to the selection of target firm rather than the change in ownership. Then, the empirical challenge in estimating the credit risk is to distinguish causality from selection. Are foreign firms simply picking certain types of acquisition targets or do foreign acquisitions change target-firm credit risk? In an attempt to control for selection into acquisition based on time-varying observable characteristics, I implement a propensity reweighting estimator to estimate the average treatment effect of foreign acquisition on credit risk.

Propensity score matching addresses a self-selection problem arising if firms' foreign-ownership status is non-random. In particular, systematic correlations between foreign-ownership and other firm characteristics could lead to biased estimates. The matching procedure controls for this potential selection bias by creating an appropriate control group of non-acquired firms and repeating the regressions using this matched sample.

Ideally, we would like to compare the credit risk of a firm that receives foreign investment to the credit risk of the firm's identical twin with no foreign investment. Asking the counterfactual question: what would have happened to those firms that did, in fact, receive foreign ownership, if they had not received it? Although this exact counterfactual is not naturally observable, propensity score matching, which involves selecting a control group of non-acquired firms closely matched to the treatment group of foreign-acquired firms, is one way to generate sets of such twins artificially. A firm is selected into the control group if it is sufficiently similar to the acquired firms on the basis of the key determinants of the acquisition decision. In other words, the goal is to find a set of control firms that are a priori equally likely to be acquired by a foreign market firm as those firms which ultimately are acquired. Appendix B provides more information on the steps followed in propensity score matching methodology.

The propensity score matching paired with difference-in-differences results are presented in Table 3.12. Consistent with previous findings, the estimates indicate that the CDS spread for acquired firms increases significantly compared to matched non-acquired firms which are consistent with previous results. In particular, the CDS spread increases by 0.20 (22 basis points) for the acquired firms relative to the matched sample and also relative to pre-acquisition period.

### 3.8.3 Multiple Transactions

Over the sample period, several target firms experience multiple acquisitions. In the main analysis, I use only the first acquisitions in analyzing the effect of block purchases on targets credit risk. Table 3.13, column (1) provides outcome results that include all transactions involving each target firm. The significant level of the estimates remains unchanged compared with those obtained from the whole sample. Table 3.13, column (2) contains the results for the sample that includes only target firms that receive second acquisitions, and they are similar to those in the whole sample. The results indicate that the CDS spread rise after a foreign block purchase is followed by a similar increase in spread for the next foreign acquirer making an acquisition in the same target firm. I also perform an additional robustness check that involves only acquiring firms located in Canada and UK. The results Table 3.13 column (3) in are different in magnitude to that full sample and statistically significant.

### 3.8.4 Failed Transactions

SDC Platinum provides information about acquisitions that are announced but withdrawn. Using this sample of failed transactions, I examine whether the firms that were potential acquisition targets differ from non-acquired firms. If it is foreign ownership that drives the post-acquisition credit risk of the acquired firms, the credit risk of failed transactions of both domestic and foreign should perform similarly, since the foreign acquisition was never successfully completed. The results in Table 3.13, column (4), indicate that the credit risk change of foreign failed transactions is similar to domestic failed transactions, a strong indication that post-acquisition increase in credit risk of target firms is driven by the respective changes in ownership status.

## 3.9 Conclusion

This paper examines the impact of foreign block acquisitions on credit risk of target firms in the U.S. In particular, I use transaction-level M&A information and CDS market data along with firm-level financial statement data to examine the change in credit risk of publicly listed U.S. targets. Using firm-level evidence, I find a significant and positive association between firm-level credit risk and the creation of sizeable foreign ownership stakes. My results provide strong evidence on a causal effect from foreign block acquisitions to credit risk using different identification techniques such as difference-in-differences, triple differences, and propensity score matching. The results indicate that on average foreign-acquired firms compared with U.S.-acquired firms experience a significant increase in CDS spreads of up to 42 basis points following the acquisitions. Over the subsequent 5 years, the CDS spread increases by 35 basis points in year five for the foreign-acquired firms compared to domestic-acquired ones relative to the year prior the acquisition. When I grouped the sample by acquirer and deal characteristics, the post-acquisition ownership percentage and the deals in which acquirer and target firm are from different industry are the most striking driver of credit risk, exhibiting manifest differences between foreign and domestic acquisitions. Finally, comparing foreign-acquired firms with domestic-acquired firms, the two groups do differ significantly in terms of post-acquisition stock volatility.

One reason why foreign acquisitions might increase firm-level credit risk is related to the role of asymmetric information. When there is more asymmetric information, managers are better able to hide potentially value-decreasing activities from outside shareholders.

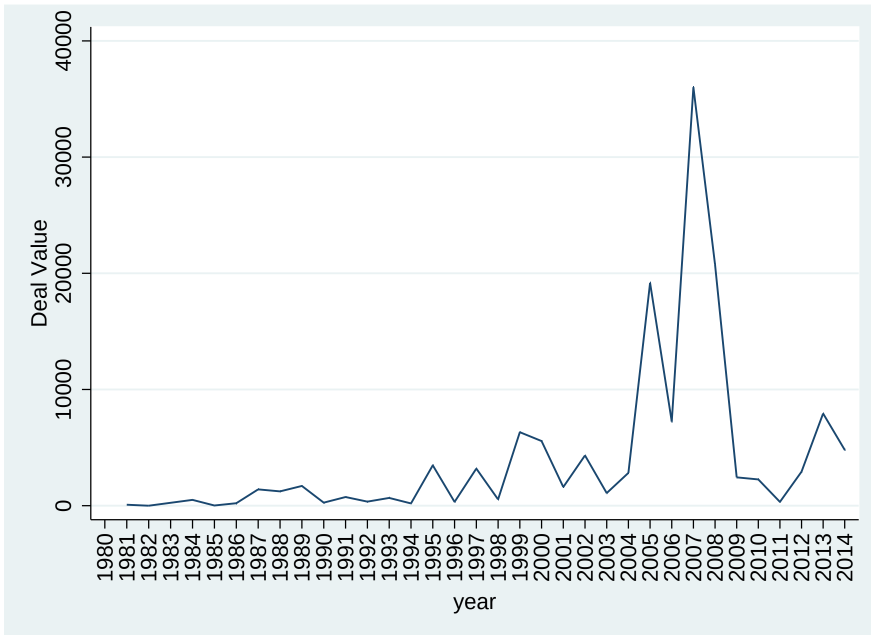
Consistent with this view, I find a larger effect for the U.S firms that are acquired by foreign investors who are in a position of informational disadvantages by being either more geographically distant or more culturally different. This evidence supports an asymmetric information explanation whereby the reduced ability of investors to monitor the managers exacerbates risk-shifting. This interpretation is reinforced by the evidence that a large increase is also observed in idiosyncratic stock volatility, which may make it easier for managers to hide risk increasing actions since they might simply be interpreted as reflecting a random outcome of greater ex-ante uncertainty (Dierkens et al., 1991). I also provide further evidence for the increased uncertainty regarding the prospect of acquired firms by a surge in the dispersion of analysts' earnings forecast.

This paper provides a novel evidence that foreign ownership has a positive impact on the credit risk of the target firms. The findings provide new insights into the literature on the consequences of foreign ownership. In particular, for governments that are devising policies toward foreign takeovers, these results do not necessarily imply that foreign ownership is undesirable due to triggering higher CDS premiums. Any policy prescription cannot overlook the beneficial role played by foreign investors in terms of firm-efficiency and productivity, corporate governance, risk-sharing, and liquidity provision. Further investigation is needed before a verdict can be reached on the overall impact of foreign ownership on financial markets.

**Figure 3.1: Developed and emerging countries acquisitions of US firms by years**

This figure presents the total value in millions of USD of foreign transactions into the United States by emerging and developed market firms for each year between 1980 and 2014 based on data from SDC.

Emerging Market Acquisitions




Developed Market Acquisitions

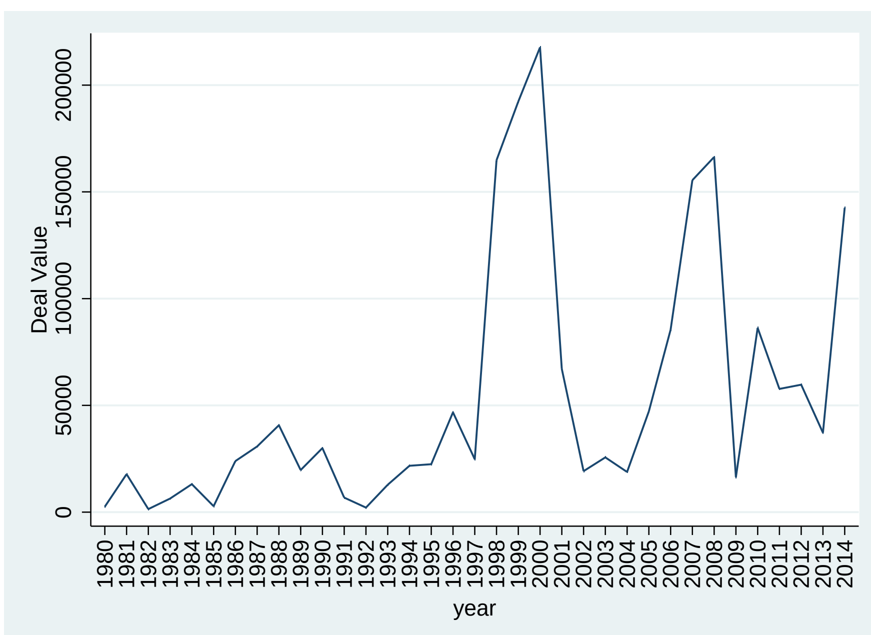


**Figure 3.2: CDS Premium**

This figure presents the average CDS premium in the log and basis points (in parenthesis) for the treatment and the control group over the weekly time series. The solid line represents the treatment group (CDS price of foreign-acquired firms) while the dashed line shows the control group (CDS price of domestic-acquired firms).

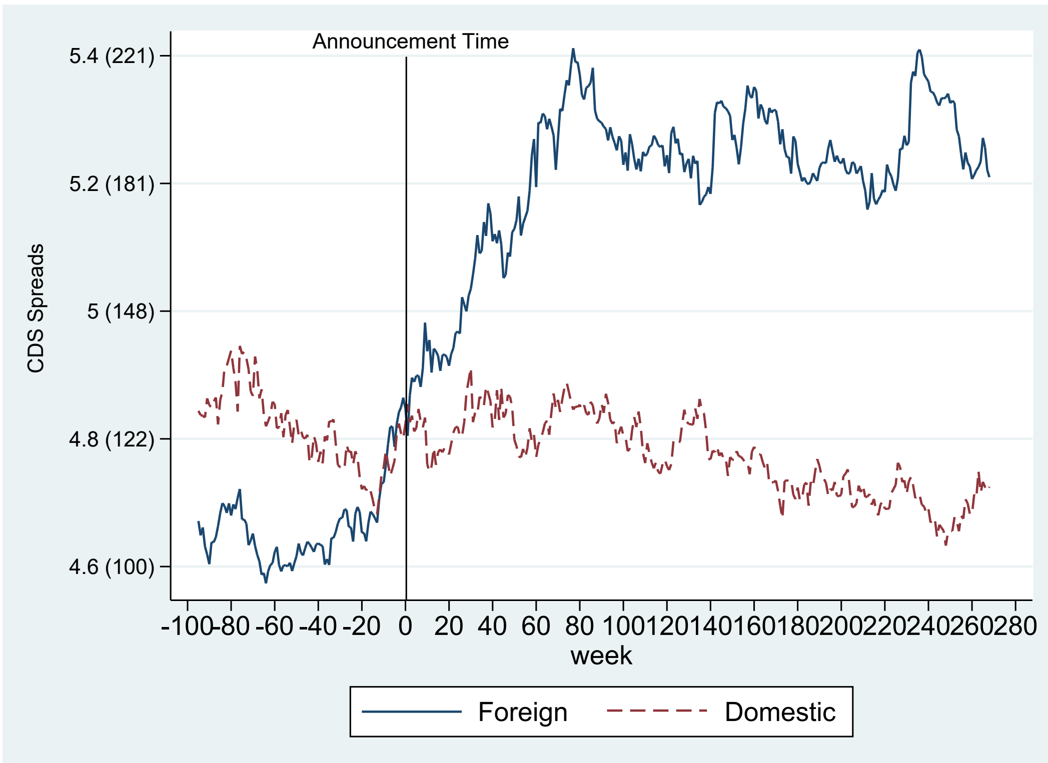


**Figure 3.3: Stock Volatility**

This figure presents the average stock volatility for the treatment and the control group over the quarterly time series. The solid line represents the treatment group (stock volatility of foreign-acquired firms) while the dashed line shows the control group (stock volatility of domestic-acquired firms).

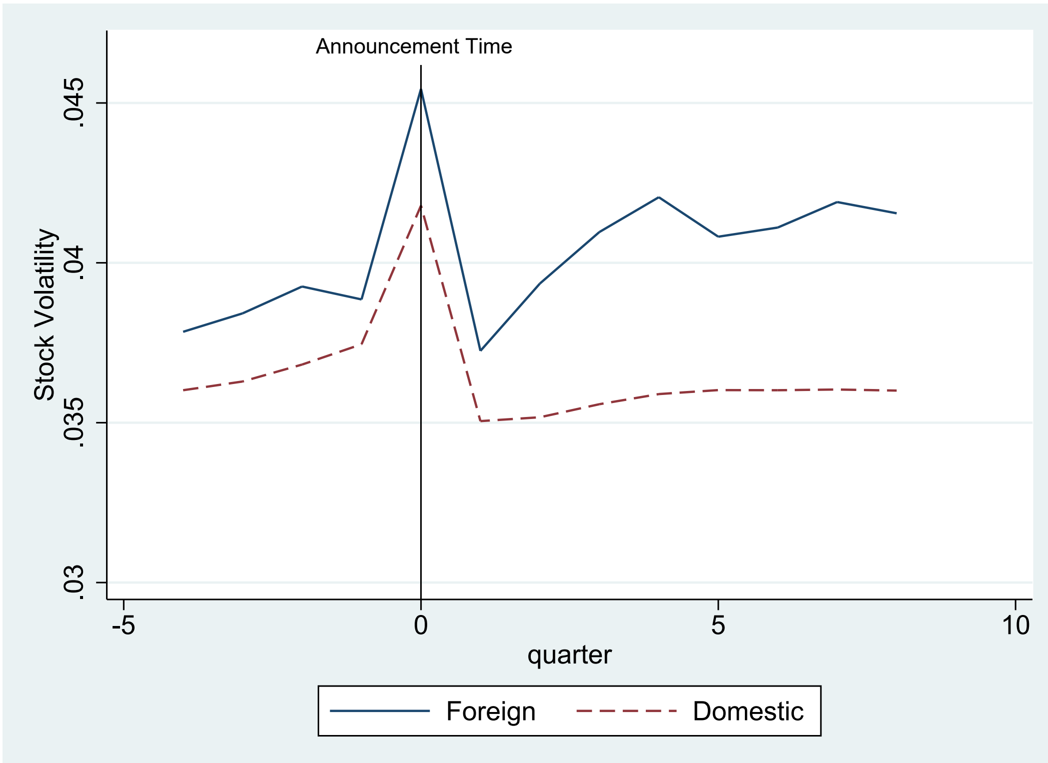


**Figure 3.4: Diversity of Opinion**

This figure presents the diversity of opinion for the foreign-acquired firms relative to domestic-acquired firms over the monthly time series. The solid line represents the diversity of opinion for foreign-acquired firms while the dashed line shows the diversity of opinion for domestic-acquired firms before and after the acquisitions.

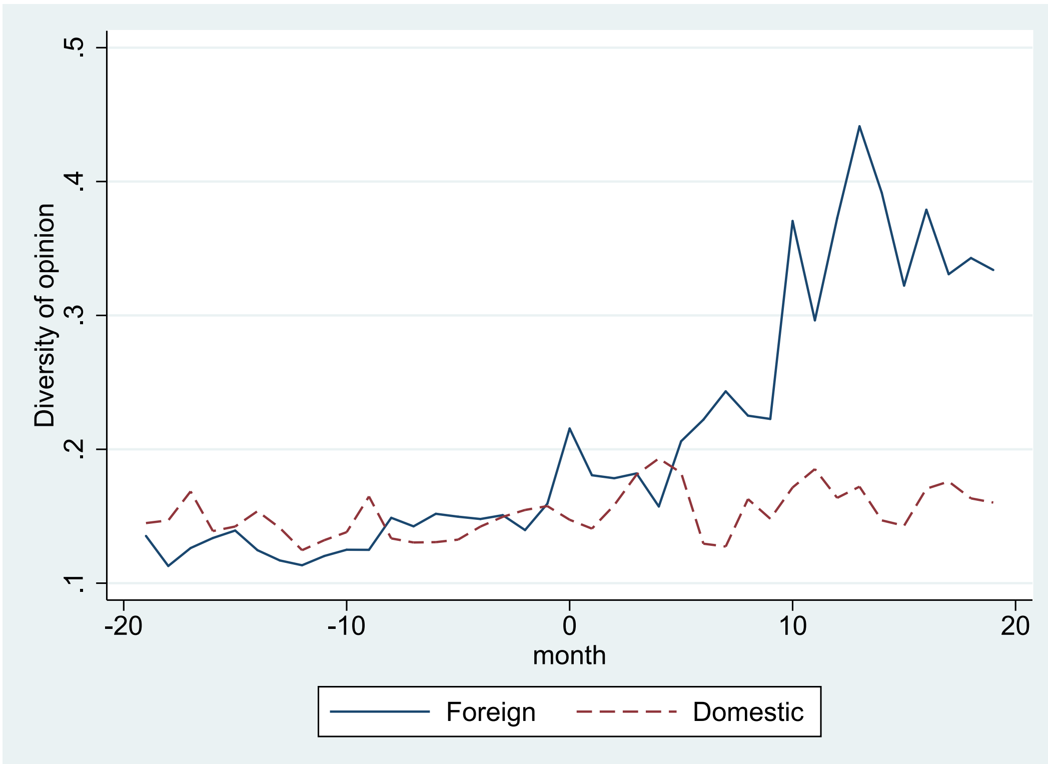
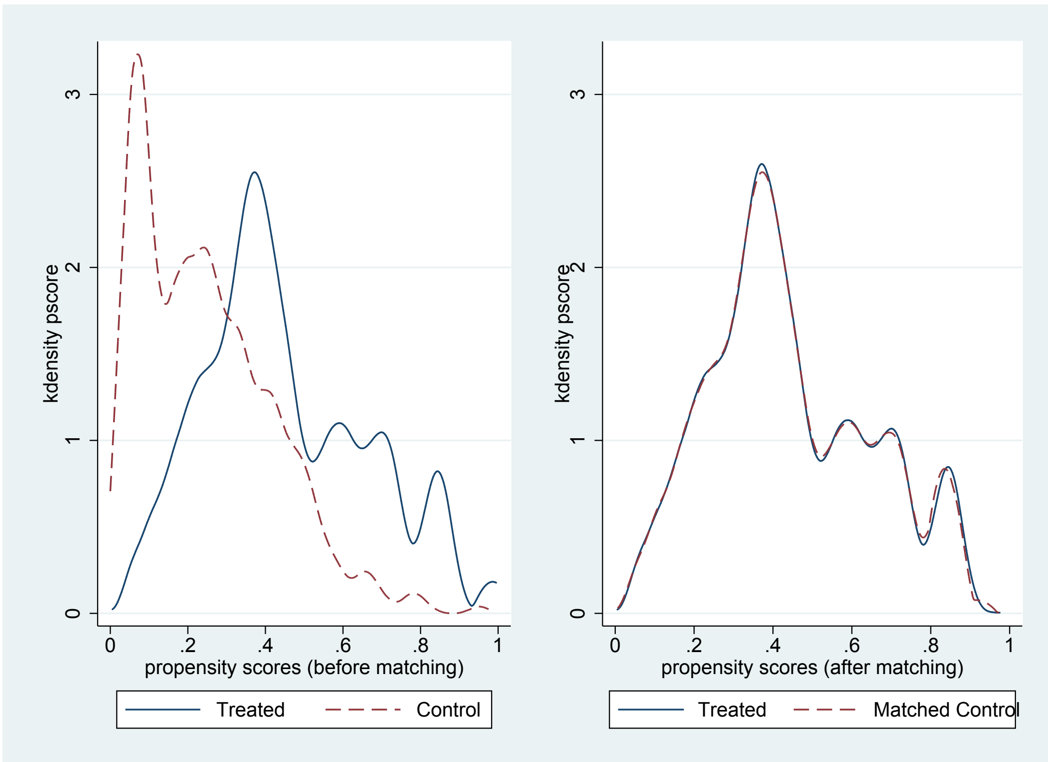


**Figure 3.5: Propensity Scores for Acquired (Treated) and Control (Matched) Firms**

This figure presents an illustration of the effects of the two-step propensity score matching approach. The two densities plotted in the left side of the figure depict the propensity score of acquisition for the acquired firms (blue) and the control firms (red, dashed) before the matching. The two densities plotted in the right side of the figure depict propensity score of acquisition for the acquired firms (blue, solid), and the reweighted propensity score matched nonacquired firms (red, dashed).



### Table 3.1: Number and Value of Acquisitions of U.S. Targets by Foreign Firms over the period 1980-2014

This table provides a break down of transactions by acquiring country. The first column lists the name of the acquiring country. The second column presents the number of transactions. The third column shows the fraction of total transactions accounted for by the acquiring country. The final column presents the total nominal transaction value in millions of US dollar by acquiring country.

| Acquirer Country | Number of Transactions | Percentance of Total Transactions | Nominal Transaction Value (in mil) |
|---|---|---|---|
| Canada | 143 | 18.43 | 76619.28906 |
| United Kingdom | 118 | 15.21 | 63155.40625 |
| Japan | 68 | 8.76 | 41567.92188 |
| France | 49 | 6.31 | 47866.35547 |
| Germany | 47 | 6.06 | 69495.52344 |
| Netherlands | 44 | 5.67 | 40926.28125 |
| Switzerland | 34 | 4.38 | 40726.83594 |
| Hong Kong | 24 | 3.09 | 1585.126953 |
| Australia | 24 | 3.09 | 19274.50977 |
| Singapore | 21 | 2.71 | 5900.73291 |
| Israel | 20 | 2.58 | 20192.28711 |
| Italy | 16 | 2.06 | 18877.47266 |
| Spain | 16 | 2.06 | 14587.49609 |
| India | 15 | 1.93 | 279.1090088 |
| Sweden | 13 | 1.68 | 3515.353027 |
| Mexico | 12 | 1.55 | 4783.926758 |
| China | 10 | 1.29 | 7562.601074 |
| Finland | 9 | 1.16 | 8936.246094 |
| Russian Federation | 9 | 1.16 | 3973.14209 |
| South Korea | 9 | 1.16 | 1874.269043 |
| Taiwan | 8 | 1.03 | 792.5809937 |
| Denmark | 8 | 1.03 | 1783.956055 |
| Republic of Ireland | 6 | 0.77 | 11481.08691 |
| Norway | 6 | 0.77 | 2673.485107 |
| Brazil | 6 | 0.77 | 2070.779053 |
| United Arab Emirates | 5 | 0.64 | 8527.222656 |
| New Zealand | 4 | 0.52 | 6295.236816 |
| Belgium | 4 | 0.52 | 52237.33594 |
| Saudi Arabia | 3 | 0.39 | 435 |
| South Africa | 3 | 0.39 | 578.8939819 |
| Luxembourg | 3 | 0.39 | 378.0280151 |
| Austria | 2 | 0.26 | 1199.875 |
| Kuwait | 2 | 0.26 | 4.445000172 |
| Argentina | 2 | 0.26 | 5307.73584 |
| Egypt | 2 | 0.26 | 8.904999733 |
| Thailand | 1 | 0.13 | 27.12000084 |
| Ecuador | 1 | 0.13 | 0 |
| Costa Rica | 1 | 0.13 | 12.5 |
| Uganda | 1 | 0.13 | 0.680000007 |
| Qatar | 1 | 0.13 | 0 |
| Bahrain | 1 | 0.13 | 100 |
| Oman | 1 | 0.13 | 0 |
| Iceland | 1 | 0.13 | 114.6940002 |
| Papua New Guinea | 1 | 0.13 | 2.700000048 |
| Venezuela | 1 | 0.13 | 7 |
| Philippines | 1 | 0.13 | 0 |
| Total | 776 | 100.00 | 585739.1462 |

**Table 3.2: Summary statistics**

This table reports summary statistics of the main variables employed in the paper. The sample includes 863 completed block acquisitions (180 foreign and 683 domestic) for the period 2001-2014. I obtain CDS data from Markit, accounting data from Compustat and stock market data from the CRSP database. Panel A presents the descriptive statistics of the variables over the entire sample. Panel B and C presents the descriptive statistics for foreign-acquired and domestically acquired firms respectively. Refer to Appendix A for variable definitions.

(Panel A: Whole Sample)

| | Mean | Std. dev. | Min | Q1 | Med. | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| CDS Spreads (bps) | 223.123 | 270.538 | 9.921 | 49.409 | 119.832 | 287.223 | 1469.933 | 210375 |
| Liquidity | 1.574 | 0.622 | 0.693 | 1.098 | 1.609 | 1.945 | 3.332 | 210375 |
| Size | 9.158 | 1.137 | 3.631 | 8.320 | 9.134 | 9.956 | 12.247 | 210375 |
| Leverage | 0.529 | 0.207 | 0.073 | 0.416 | 0.505 | 0.608 | 4.937 | 210375 |
| ROA | 0.138 | 0.079 | -1.691 | 0.091 | 0.127 | 0.178 | 0.678 | 210375 |
| Vol | 0.024 | 0.018 | 0.006 | .0144 | 0.020 | 0.028 | 1.163 | 210375 |

(Panel B: Foreign Acquired Firms)

| | Mean | Std. dev. | Min | Q1 | Med. | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| CDS Spreads (bps) | 249.304 | 292.303 | 9.921 | 51.232 | 137.247 | 335.875 | 1469.933 | 43879 |
| Liquidity | 1.618 | 0.595 | 0.693 | 1.098 | 1.609 | 1.945 | 3.332 | 43879 |
| Size | 9.062 | 0.919 | 5.983 | 8.350 | 9.090 | 9.786 | 11.914 | 43879 |
| Leverage | 0.496 | 0.173 | 0.074 | 0.389 | 0.483 | 0.599 | 3.042 | 43879 |
| ROA | 0.130 | 0.076 | -0.207 | 0.085 | 0.118 | 0.162 | 0.581 | 43879 |
| Vol | 0.024 | 0.013 | 0.006 | 0.015 | 0.021 | 0.029 | 0.117 | 43879 |

(Panel C: Domestically Acquired Firms)

| | Mean | Std. dev. | Min | Q1 | Med. | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| CDS Spreads (bps) | 213.667 | 261.59 | 9.921 | 48.752 | 115.616 | 274.631 | 1469.933 | 166496 |
| Liquidity | 1.558 | 0.631 | 0.693 | 1.098 | 1.609 | 1.945 | 3.332 | 166496 |
| Size | 9.193 | 1.204 | 3.630 | 8.301 | 9.143 | 10.066 | 12.247 | 166496 |
| Leverage | 0.541 | 0.216 | 0.072 | 0.431 | 0.513 | 0.612 | 4.937 | 166496 |
| ROA | 0.140 | 0.081 | -1.691 | 0.092 | 0.131 | 0.180 | 0.677 | 166496 |
| Vol | 0.023 | 0.019 | 0.006 | 0.014 | 0.019 | 0.028 | 1.162 | 166496 |

**Table 3.3: Effect of foreign block acquisitions on target firms' CDS spreads.**

This table reports difference-in-differences estimates for the post-acquisition CDS premiums between foreign-acquired (entire sample in Column (1), developed countries in Column (2) and emerging countries in Column (3)) and control (domestic-acquired) firms. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>All Countries<br>ln(CDS) | (2)<br>Developed Countries<br>ln(CDS) | (3)<br>Emerging Countries<br>ln(CDS) |
|---|---|---|---|
| $Post * Foreign$ | 0.336*** | 0.365*** | 0.276* |
| | (3.33) | (2.88) | (1.77) |
| $Liquidity$ | 0.0302 | 0.0328 | 0.0378 |
| | (0.96) | (1.02) | (1.00) |
| $Size$ | 0.0375 | 0.0629 | 0.0669 |
| | (0.72) | (1.16) | (1.16) |
| $Leverage$ | 1.079*** | 0.995*** | 0.913*** |
| | (5.00) | (4.67) | (3.61) |
| $ROA$ | -5.620*** | -5.380*** | -6.157*** |
| | (-5.13) | (-4.78) | (-5.17) |
| $Vol$ | 0.0144*** | 0.0137*** | 0.0139*** |
| | (10.87) | (10.11) | (9.34) |
| $Constant$ | 4.079*** | 3.868*** | 3.950*** |
| | (8.33) | (7.63) | (7.39) |
| N | 128687 | 120652 | 99863 |
| R-squared | 0.826 | 0.829 | 0.830 |
| Rating FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm |

**Table 3.4: Effect of foreign block acquisitions on target firms' CDS spreads over 1-5 year window.**

This table reports difference-in-differences estimates for the post-acquisition CDS premiums between foreign-acquired and control (domestic-acquired) firms over five years window following the acquisitions. I set $t = 0$ for the weeks in the year of acquisition, for the weeks in the years following the acquisition $t = 1, ..., 5$, and for the weeks in the year prior to the acquisition, $t = -1$, etc. The dependent variable is the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>ln(CDS) | (2)<br>ln(CDS) | (3)<br>ln(CDS) | (4)<br>ln(CDS) | (5)<br>ln(CDS) |
|---|---|---|---|---|---|
| $Post * Foreign\_1$ | 0.167* | | | | |
| | (1.67) | | | | |
| $Post * Foreign\_2$ | | 0.182* | | | |
| | | (1.77) | | | |
| $Post * Foreign\_3$ | | | 0.221** | | |
| | | | (2.07) | | |
| $Post * Foreign\_4$ | | | | 0.254** | |
| | | | | (2.25) | |
| $Post * Foreign\_5$ | | | | | 0.299** |
| | | | | | (2.59) |
| *Liquidity* | 0.00367 | -0.00618 | 0.00499 | 0.0226 | 0.0409 |
| | (0.09) | (-0.14) | (0.11) | (0.49) | (0.89) |
| *Size* | 0.0740 | 0.0967 | 0.122 | 0.128 | 0.164 |
| | (0.32) | (0.40) | (0.57) | (0.65) | (1.02) |
| *Leverage* | 1.453*** | 1.395*** | 1.055*** | 0.728** | 0.649* |
| | (3.29) | (3.49) | (2.90) | (2.08) | (1.87) |
| *ROA* | -4.507** | -3.693** | -4.191** | -4.593*** | -4.783*** |
| | (-2.44) | (-2.07) | (-2.38) | (-2.76) | (-3.03) |
| *Vol* | 0.0139*** | 0.0140*** | 0.0151*** | 0.0142*** | 0.0138*** |
| | (3.89) | (4.14) | (4.74) | (4.71) | (4.90) |
| *Constant* | 3.847** | 3.306 | 3.502* | 3.678** | 3.438** |
| | (2.00) | (1.59) | (1.91) | (2.17) | (2.49) |
| N | 11788 | 13883 | 16163 | 18448 | 20557 |
| R-squared | 0.895 | 0.896 | 0.890 | 0.891 | 0.891 |
| Rating FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm | Firm |

**Table 3.5: Target firms' CDS spreads change across various groupings by transaction characteristics.**

This table reports difference-in-differences estimates for the post-acquisition chance in CDS premiums between foreign-acquired firms and domestic-acquired firms. Each panel reports post-acquisition change in CDS spreads for each subgroups consisting of: majority and minority control acquisitions, firms not in the same industry as the acquiring firm (diversifying) and horizontal acquisition, and acquisitions financed solely by cash. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>Majority<br>ln(CDS) | (2)<br>Minority<br>ln(CDS) | (3)<br>Horizontal<br>ln(CDS) | (4)<br>Diversifying<br>ln(CDS) | (5)<br>Cash Only<br>ln(CDS) |
|---|---|---|---|---|---|
| $Post * Foreign$ | 0.325*** | 0.152 | 0.0970 | 0.336*** | 0.0734 |
| | (2.66) | (1.04) | (0.70) | (2.82) | (0.55) |
| $Liquidity$ | 0.0899** | -0.0455 | 0.0881* | -0.00357 | 0.00607 |
| | (2.30) | (-0.88) | (1.93) | (-0.09) | (0.14) |
| $Size$ | -0.245*** | -0.108 | -0.125 | -0.219*** | -0.275*** |
| | (-2.97) | (-1.44) | (-1.36) | (-3.14) | (-3.03) |
| $Leverage$ | 1.231*** | 1.403*** | 1.001*** | 1.493*** | 1.566*** |
| | (5.16) | (4.42) | (3.51) | (5.78) | (4.34) |
| $ROA$ | -3.627*** | -2.156*** | -2.232*** | -4.018*** | -2.171** |
| | (-7.74) | (-3.08) | (-3.61) | (-8.35) | (-2.29) |
| $Vol$ | 4.054* | 13.75*** | 10.72*** | 4.293* | 18.55*** |
| | (1.87) | (3.25) | (3.52) | (1.77) | (5.71) |
| $Constant$ | 6.482*** | 5.015*** | 5.399*** | 6.129*** | 6.337*** |
| | (8.19) | (6.78) | (6.08) | (9.21) | (7.16) |
| N | 73735 | 45069 | 54270 | 64534 | 35900 |
| R-squared | 0.823 | 0.815 | 0.827 | 0.817 | 0.843 |
| Rating FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm | Firm |

**Table 3.6: Target firms' CDS spreads change across differences in subgroups.**

This table reports nested models estimates (e.g., $Post_{i,t} * Foreign_{i,t} * Stake_{i,t}$) to assess the differences in subgroups. Each panel reports post-acquisition change in CDS spreads for differences in subgroups consisting of: developed vs. emerging countries (where $Dev_{i,t}$ is equal to 1 for developed countries and zero otherwise), majority vs. minority control acquisitions (where $Maj_{i,t}$ is equal to 1 for majority controls and zero otherwise), diversifying vs. horizontal acquisition (where $Div_{i,t}$ is equal to 1 for diversifying deals and zero otherwise), and acquisitions financed solely by cash vs. others (where $Cash_{i,t}$ is equal to 1 for cash payment and zero otherwise) respectively. Interaction, $Post_{i,t} * Foreign_{i,t}$, is same as in difference-in-differences. Note that other interaction terms ($Post_{i,t} * Stake_{i,t}$ and $Foreign_{i,t} * Stake_{i,t}$) are omitted because of collinearity. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1) Developed vs. Emerging ln(CDS) | (2) Majority vs. Minority ln(CDS) | (3) Diversifying vs. Horizontal ln(CDS) | (4) Cash vs. Others ln(CDS) |
|---|---|---|---|---|
| $Post * Foreign * Dev$ | -0.0382 | | | |
| | (-0.54) | | | |
| $Post * Foreign * Maj$ | | 0.134* | | |
| | | (1.67) | | |
| $Post * Foreign * Div$ | | | 0.0721 | |
| | | | (0.87) | |
| $Post * Foreign * Cash$ | | | | -0.0145 |
| | | | | (-0.17) |
| $Post * Foreign$ | 0.156** | 0.0709* | 0.0879 | 0.0935 |
| | (2.51) | (1.69) | (1.24) | (1.09) |
| $Liquidity$ | 0.0236 | 0.0248 | 0.0236 | 0.00498 |
| | (0.71) | (0.75) | (0.71) | (0.14) |
| $Size$ | -0.176*** | -0.177*** | -0.175*** | -0.195*** |
| | (-2.78) | (-2.81) | (-2.76) | (-2.78) |
| $Leverage$ | 1.465*** | 1.465*** | 1.463*** | 1.524*** |
| | (6.43) | (6.44) | (6.43) | (6.29) |
| $ROA$ | -2.900*** | -2.897*** | -2.899*** | -2.538*** |
| | (-4.01) | (-4.02) | (-4.01) | (-3.10) |
| $Vol$ | 5.631* | 5.625* | 5.619* | 6.691** |
| | (1.87) | (1.87) | (1.87) | (2.07) |
| $Constant$ | 5.795*** | 5.814*** | 5.788*** | 5.935*** |
| | (9.62) | (9.63) | (9.61) | (9.07) |
| N | 165062 | 164969 | 165062 | 107539 |
| R-squared | 0.827 | 0.828 | 0.827 | 0.830 |
| Rating FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm |

**Table 3.7: Effect of foreign block acquisitions on target firms' stock volatility.**

This table reports the difference-in-differences estimates for the post-acquisition change in stock volatility between foreign-acquired and control (domestic-acquired) firms. The dependent variables are total volatility (Vol), and its systematic (Sys_vol)and idiosyncratic component (Idio_vol_m, or Idio_vol_f). In addition to relevant independent variables, regressions contain firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>Vol | (2)<br>Sys_vol | (3)<br>Idio_vol_m | (4)<br>Idio_vol_f |
|---|---|---|---|---|
| $Post * Foreign$ | 0.00242*** | -0.00164 | 0.00253*** | 0.00249*** |
| | (3.14) | (-0.08) | (3.31) | (3.27) |
| $Ln(mc)$ | -0.00468*** | 0.0115** | -0.00508*** | -0.00511*** |
| | (-26.07) | (2.55) | (-28.40) | (-28.57) |
| $A - ratio$ | 159.5*** | 12.50 | 159.9*** | 159.9*** |
| | (3.09) | (0.21) | (3.07) | (3.07) |
| $1/price$ | 0.0000150 | 0.000242 | 0.0000151 | 0.0000152 |
| | (1.23) | (0.96) | (1.22) | (1.23) |
| $P6M - ret$ | 0.0107 | -0.575 | 0.0123 | 0.0117 |
| | (0.84) | (-0.54) | (0.98) | (0.93) |
| $BM$ | -0.00190 | -0.0331 | -0.00187 | -0.00186 |
| | (-1.17) | (-1.05) | (-1.15) | (-1.14) |
| $Constant$ | 0.0609*** | 0.0447 | 0.0617*** | 0.0616*** |
| | (48.60) | (0.91) | (49.48) | (49.37) |
| N | 398649 | 398336 | 398649 | 398649 |
| R-squared | 0.495 | 0.0785 | 0.500 | 0.499 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm |

**Table 3.8: Robustness check: Effect of foreign block acquisitions on target firms' stock volatility.**

This table reports the difference-in-difference-in-differences (DDD). The dependent variables are total volatility (Vol), and its systematic (Sys_vol)and idiosyncratic component (Idio_vol_m, or Idio_vol_f). In addition to relevant independent variables, regressions contain firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>Vol | (2)<br>Sys_vol | (3)<br>Idio_vol_m | (4)<br>Idio_vol_f |
|---|---|---|---|---|
| $Post * Treated * Foreign$ | 0.00244*** | -0.00154 | 0.00255*** | 0.00251*** |
| | (3.15) | (-0.08) | (3.32) | (3.28) |
| $Post * Treated$ | -0.00132*** | -0.0399* | -0.00119*** | -0.00120*** |
| | (-4.57) | (-1.81) | (-4.17) | (-4.20) |
| $Ln(mc)$ | -0.00511*** | 0.0125*** | -0.00550*** | -0.00553*** |
| | (-30.81) | (3.47) | (-33.34) | (-33.53) |
| $A - ratio$ | 3.220 | 4.894 | 3.271 | 3.244 |
| | (1.01) | (0.66) | (1.02) | (1.01) |
| $1/price$ | 0.00000530 | 0.0000763 | 0.00000549 | 0.00000555 |
| | (0.92) | (0.83) | (0.95) | (0.96) |
| $P6M - ret$ | 0.0140 | -0.536 | 0.0155 | 0.0151 |
| | (1.17) | (-0.74) | (1.30) | (1.27) |
| $BM$ | 0.000000448 | -0.0000126 | -0.000000585 | -0.000000228 |
| | (0.17) | (-0.26) | (-0.22) | (-0.08) |
| $Constant$ | 0.0662*** | 0.0201 | 0.0671*** | 0.0670*** |
| | (58.17) | (0.55) | (59.22) | (59.11) |
| N | 522501 | 521537 | 522501 | 522501 |
| R-squared | 0.488 | 0.0790 | 0.493 | 0.492 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm |

**Table 3.9: The role of Diversity of Opinion (DOP) and proxy of asymmetric information measures (Idio_vol_m or Idio_vol_f) in credit risk.**

This table reports the role of diversity of opinion and asymmetric information measures in log CDS premiums. DOP is the dispersion in analysts' earnings forecasts as a proxy for the diversity of opinion, while Idio_vol_m and Idio_vol_f are the proxies for the asymmetric information. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1) ln(CDS) | (2) ln(CDS) | (3) ln(CDS) | (4) ln(CDS) | (5) ln(CDS) |
|---|---|---|---|---|---|
| *DOP* | 0.150*** | | | 0.124*** | 0.125*** |
| | (3.57) | | | (3.08) | (3.09) |
| *Idio_vol_m* | | 15.62*** | | 15.53*** | |
| | | (17.50) | | (17.41) | |
| *Idio_vol_f* | | | 15.53*** | | 15.45*** |
| | | | (16.88) | | (16.81) |
| *Liquidity* | 0.0490* | 0.0501* | 0.0511* | 0.0497* | 0.0508* |
| | (1.71) | (1.76) | (1.80) | (1.75) | (1.79) |
| *Size* | -0.146** | -0.138** | -0.142** | -0.142** | -0.146** |
| | (-2.41) | (-2.28) | (-2.34) | (-2.35) | (-2.41) |
| *Leverage* | -0.0212 | -0.0230 | -0.0231 | -0.0240 | -0.0241 |
| | (-0.40) | (-0.44) | (-0.44) | (-0.46) | (-0.46) |
| *ROA* | -3.277*** | -3.250*** | -3.261*** | -3.262*** | -3.273*** |
| | (-6.37) | (-6.41) | (-6.40) | (-6.40) | (-6.38) |
| *Vol* | 19.95*** | 4.919** | 5.518** | 4.695** | 5.294** |
| | (7.71) | (2.22) | (2.44) | (2.11) | (2.33) |
| *Constant* | 5.766*** | 5.615*** | 5.633*** | 5.663*** | 5.681*** |
| | (9.33) | (9.16) | (9.17) | (9.21) | (9.22) |
| N | 122568 | 122529 | 122529 | 122529 | 122529 |
| R-squared | 0.833 | 0.841 | 0.841 | 0.842 | 0.841 |
| Rating FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm | Firm |

**Table 3.10: Effect of geographic distance (GD) and cultural differences (CD) on target firms' post-acquisition CDS spreads.**

This table reports the role of geographic distance (GD) and cultural differences (CD), proxies of asymmetric information, in CDS premiums. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>ln(CDS) | (2)<br>ln(CDS) | (3)<br>ln(CDS) |
|---|---|---|---|
| $Post * GD$ | 0.0331*** | | 0.0373* |
| | (3.07) | | (1.70) |
| $Post * CD$ | | 0.145* | 0.0139 |
| | | (1.83) | (0.12) |
| $Liquidity$ | 0.0364 | 0.0109 | 0.0127 |
| | (1.11) | (0.28) | (0.33) |
| $Size$ | -0.190*** | -0.207*** | -0.204*** |
| | (-3.34) | (-3.19) | (-3.13) |
| $Leverage$ | 1.335*** | 1.071*** | 1.074*** |
| | (6.53) | (4.54) | (4.54) |
| $ROA$ | -3.133*** | -3.270*** | -3.220*** |
| | (-6.69) | (-9.68) | (-9.72) |
| $Vol$ | 5.517* | 12.90*** | 12.63*** |
| | (1.92) | (5.10) | (5.06) |
| $Constant$ | 5.932*** | 6.004*** | 5.992*** |
| | (10.54) | (9.36) | (9.33) |
| N | 118804 | 112572 | 112572 |
| R-squared | 0.818 | 0.833 | 0.834 |
| Rating FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm |

**Table 3.11: Robustness check: Effect of foreign block acquisitions on target firms' CDS spreads.**

This table reports the difference-in-difference-in-differences (DDD) estimates. The interaction, $Post_{i,t} * Treated_{i,t} * Foreign_{i,t}$, is equal to 1 for foreign acquired firms and post-acquisition period. Note that other DD interaction terms ($Post_{i,t} * Foreign_{i,t}$ and $Foreign_{i,t} * Treated_{i,t}$) are omitted because of collinearity. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>All Countries<br>ln(CDS) | (2)<br>Developed Countries<br>ln(CDS) | (3)<br>Emerging Countries<br>ln(CDS) |
|---|---|---|---|
| $Post * Treated * Foreign$ | 0.255* | 0.306* | 0.129 |
| | (1.71) | (1.75) | (0.60) |
| $Post * Treated$ | 0.0727 | 0.0679 | 0.0721 |
| | (0.83) | (0.78) | (0.84) |
| $Liquidity$ | 0.00173 | 0.00678 | 0.00306 |
| | (0.05) | (0.19) | (0.08) |
| $Size$ | 0.00830 | 0.0239 | 0.0662 |
| | (0.14) | (0.39) | (1.11) |
| $Leverage$ | 1.321*** | 1.225*** | 1.251*** |
| | (6.07) | (5.73) | (5.16) |
| $ROA$ | -5.421*** | -5.176*** | -6.072*** |
| | (-4.71) | (-4.42) | (-5.08) |
| $Vol$ | 0.0143*** | 0.0134*** | 0.0142*** |
| | (8.77) | (8.05) | (7.65) |
| $Constant$ | 4.068*** | 3.936*** | 3.517*** |
| | (7.47) | (6.78) | (6.17) |
| N | 104390 | 98020 | 82190 |
| R-squared | 0.839 | 0.840 | 0.847 |
| Rating FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm |

**Table 3.12: Robustness check: Effect of foreign block acquisitions on target firms' CDS spreads.**

This table reports propensity score matching (PSM) estimates for the log CDS premiums between foreign-acquired and matched control firms following the acquisitions. The propensity score is calculated based on a probit regression model with the relevant controls and fixed effects factors as the independent variables and the dummy variable (1 for foreign acquisitions and 0 for domestic acquisitions) as the dependent variable. Based on the calculated propensity scores of each firm, I match the nonacquired firms with the foreign-acquired firms and run difference-in-differences. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1)<br>All Countries<br>ln(CDS) | (2)<br>Developed Countries<br>ln(CDS) | (3)<br>Emerging Countries<br>ln(CDS) |
|---|---|---|---|
| $Post * Foreign$ | 0.201** | 0.243** | 0.0684 |
| | (2.20) | (2.07) | (0.51) |
| $Liquidity$ | 0.0544* | 0.0584* | 0.0529* |
| | (1.76) | (1.95) | (1.71) |
| $Size$ | -0.0438 | -0.0376 | -0.0627 |
| | (-0.67) | (-0.57) | (-0.94) |
| $Leverage$ | 1.838*** | 1.837*** | 1.826*** |
| | (9.08) | (9.16) | (8.94) |
| $ROA$ | -5.041*** | -5.027*** | -5.079*** |
| | (-4.42) | (-4.43) | (-4.40) |
| $Vol$ | 0.0122*** | 0.0123*** | 0.0123*** |
| | (7.01) | (7.01) | (6.83) |
| $Constant$ | 4.373*** | 4.332*** | 4.570*** |
| | (7.42) | (7.22) | (7.63) |
| N | 107448 | 107448 | 107448 |
| R-squared | 0.828 | 0.829 | 0.827 |
| Rating FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm |

**Table 3.13: Additional Tests: Target firms' CDS spreads change across various groupings by transaction characteristics.**

This table reports the difference-in-difference estimates for the post-acquisition CDS premiums between foreign-acquired and domestic-acquired firms, for multiple acquisitions, for second acquisition, for the sample only including Canada and UK or for which the deal was withdrawn respectively. The dependent variables are the log CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA) and stock volatility. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | (1) Multiple Acquisitions ln(CDS) | (2) Second Acquisition ln(CDS) | (3) Canada and UK ln(CDS) | (4) Failed Transactions ln(CDS) |
|---|---|---|---|---|
| $Post * Foreign$ | 0.135*** | 0.115** | 0.194* | 0.0265 |
| | (3.19) | (2.56) | (1.69) | (0.37) |
| $Liquidity$ | 0.0238 | 0.0156 | 0.0321 | 0.0306 |
| | (0.71) | (0.37) | (0.90) | (0.69) |
| $Size$ | -0.176*** | -0.148* | -0.182*** | -0.310*** |
| | (-2.78) | (-1.86) | (-2.68) | (-3.29) |
| $Leverage$ | 1.464*** | 1.466*** | 1.464*** | 0.699** |
| | (6.43) | (4.59) | (5.74) | (2.37) |
| $ROA$ | -2.902*** | -3.054*** | -2.804*** | -3.801*** |
| | (-4.02) | (-3.88) | (-3.52) | (-5.44) |
| $Vol$ | 5.632* | 3.703* | 4.903* | 17.33*** |
| | (1.87) | (1.80) | (1.84) | (4.02) |
| $Constant$ | 5.799*** | 5.681*** | 5.898*** | 6.782*** |
| | (9.62) | (7.23) | (9.05) | (7.72) |
| N | 210375 | 47389 | 168266 | 47960 |
| R-squared | 0.827 | 0.817 | 0.820 | 0.827 |
| Rating FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm |

## Appendix A: Definition of Variables

| Variable | Description | Source |
|---|---|---|
| $Ln(CDS)$ | The natural logarithm of 5-year CDS spread. | Markit |
| $Post * Foreign$ | A dummy variable equal to one if a firm is acquired by foreign investors and if the time involves post-acquisition period, and zero otherwise. | |
| $Size$ | The natural logarithm of total book value of assets. | Compustat |
| $Leverage$ | Total debt (the sum of long-term and short-term debt) divided by total assets. | Compustat |
| $ROA$ | Return on assets or profitability, which is the operating income before depreciation, amortization and taxes (OIBD) divided by total assets. | Compustat |
| $Liquidity$ | Markit reports CDS depth, the number of dealers that contributed to the quote formation, which I use as a CDS-level proxy for liquidity following Qiu and Yu (2012). | Markit |
| $Vol$ | Stock return volatility, which is the standard deviation of daily stock log returns within the quarter month. | CRSP |
| $Sys\_vol$ | Systematic component of stock return volatility. | CRSP |
| $Idio\_vol\_m$ | Idiosyncratic components of stock return volatility computed from CAPM. | CRSP |
| $Idio\_vol\_f$ | Idiosyncratic components of stock return volatility calculated from FF3F. | CRSP |
| $Ln(mc)$ | The natural logarithm of market capitalization of the stock at the end of the month. | CRSP |
| $1/price$ | The inverse of the nominal share price at the end of the month. | CRSP |
| $A - ratio$ | Amihud ratio: Absolute return scaled by daily dollar volume in $ million, average within the quarter. Based on Amihud (2002). | CRSP |
| $P6M - ret$ | Past 6 month return, which is the stock's 6-month momentum return over the two quarters prior to analysis. | CRSP |
| $BM$ | Book-to-market, which is the stock's book value of equity relative to market value of equity. | CRSP, Compustat |
| $DOP$ | The dispersion in analysts' earning forecasts as a proxy for the diversity of opinion. | I/B/E/S |
| $GD$ | Geographic distance, which is the Great Circle Distance between foreign acquirer and the US targets. | mapsofworld.com |
| $CD$ | Cultural differences, which is a dummy variable if the difference between the Uncertainty Avoidance Index which is a Hofstede's culture variable, of the acquirer's country is the same or greater than that of the target's country, else zero. | Hofstede's website |

# Appendix B: Steps followed in propensity score matching methodology

The control group consists of all U.S. targets firms that did not receive investment by foreign market firms. This group includes firms that have received investment from U.S. domestic firms and firms that never received outside investment throughout the sample period. In addition, following Petkova (2008)'s approach of proportional-random acquisition time assignment, I assign counterfactual treatment dates to the firms that are not acquired by foreign. I determine the fraction of the total number of acquisitions that occur in each calendar year during my sample period, and then assign the hypothetical treatment year to the firms in the control group in the same proportion as their occurrences in the acquisition group.

The approach to constructing an appropriate comparison group of non-acquired firms involves a two-step matching process. The first step, a probit regression, estimates the probability of foreign acquisition based on covariates that drive both the acquisition decision as well as credit risk of the firm. In particular, the dependent variable of the regression model is a dummy variable that equals one if the target firm is acquired by a foreign company and equals zero for non-acquired firms. The independent variables include size, liquidity, leverage, profitability and stock volatility of the target firm that are measured in the latest fiscal year-end before the acquisitions. In addition, rating, sector (industry), region (state) and time dummies are included in the vector of control variables, where industry dummies are based on 2-digit NAICS codes and regional dummies are based on the U.S. state where the target firm is located. Industry dummies serve as controls for industry-specific performance as well as predictors of acquisition preferences. For instance, Harris and Ravenscraft (1991) argues that some acquirers prefer more R&D intensive industries, thus requiring the use of industry-fixed effects. Time dummies control for time-dependent macro factors such as the exchange rate (Harris and Ravenscraft, 1991). State dummies control for state-specific factors, such as tax benefits, affecting the acquisition status. The second step involves using the propensity scores as weights to create the control groups and combining it with a difference-in-differences approach. The matching technique allows us to take into account differences in observable characteristics across the firms in the database. This second step involves running a weighted difference-in-differences regression, using the propensity score as weights, to eliminate time-invariant and unobservable differences between the foreign-acquired firms and the control firms. Owing to the parametric nature of the second step, we can also include other covariates that explain firm performance as well as control for industry, year, and state fixed effects.

Figure 3.5 provides an illustration of the effects of the two-step propensity score matching approach. The two densities plotted in the left side of the figure depict the propensity score of acquisition for the acquired firms (blue) and the control firms (red, dashed) before the matching. The two densities plotted in the right side of the figure depict propensity score of acquisition for the acquired firms (blue), and the reweighted propensity score matched non-acquired firms (red, dashed). The matching estimator performs extremely well as evidenced by the proximity between the density of the acquired firms and that of the reweighted matched non-acquired firms.[19] The two-step matching involves constructing an appropriate counterfactual for each acquired firm given the set of observable covariates available for the firms. The propensity score provides a summary index of all the covariates combined, so that matching essentially brings the group of control firms closer to the acquired firms on all available dimensions. The propensity score matching estimator assigns more weight to control firms that are similar to the acquired firms in terms of propensity scores, which ensures that the comparisons involve firms that are very similar prior to acquisition.

Instead of treating each of the firms linearly and with the same weight, the difference-in-differences estimator combined with propensity score matching allows us to include only acquired firms within the common support and picks control firms according to the metric

[19] I also used alternative matching estimators, including the Mahalanobis distance metric and kernel matching. Results are qualitatively similar to those reported using propensity score reweighting.

function specific to the matching method. The common support refers to treated firms that do not lie above the maximum or below the minimum propensity score for the matched control group.

More formally:

1. Run Probit regression where:

(a) The dependent variable is equal to 1, if a firm is acquired by a foreign market firm; zero otherwise.

(b) Choose appropriate conditioning variables, covariates which are observable firm characteristics, which are size, liquidity, leverage, profitability and stock volatility.

(c) Obtain propensity score: predicted probability ($p$) or $log[p/(1-p)]$.

2. Generate weights using propensity scores:

(a) For foreign-acquired firms, assign $weight = 1$.

(b) For nonacquired firms, assign $weight = p/(1-p)$ using predicted probability in 1(c)).

3. Run multivariate difference-in-differences regression with the generated weights in (2) and covariates that were used in the initial probit along with firm and time fixed effects to eliminate time-invariant, unobservable differences between foreign-acquired (treated) and nonacquired (matched control) firms.

# Chapter 4

# Does Corporate Governance Matter? Evidence from the AGR Governance Rating

## 4.1 Introduction

Academic research as well as numerous commercial endeavors attempt to quantify the effectiveness of a firm's corporate governance. The resultant metrics allow users to investigate potential links between corporate governance and a firm's subsequent operating performance and its stock price behavior.

In a seminal contribution, Gompers et al. (2003a) propose the so-called G score which enumerates the number of anti-takeover measures adopted by a firm and document that a portfolio long shares of firms with strong shareholder rights (five or fewer measures and labelled as “democracies”) while shorting shares of firms with weak shareholder rights (fourteen or more measures and labelled as “dictatorships”) generates abnormal returns of 8.5% per year over the sample period 1990 to 1999. Subsequently, Bebchuk et al. (2009) put forward the E or entrenchment index which relies on a subset of six of the twenty-four provisions considered in the G score that are most highly correlated with firm value and stockholder returns. They find that buying a portfolio of stocks of firms with non-entrenched management (a zero E index score) and selling short a portfolio of stocks of firms with entrenched management (a five or six E index score) earned abnormal returns of 7% annually over the 1990 to 2003 sample.

Although both the G and E measures have been widely cited and used, unfortunately the effects of governance on a firm' operating performance and stock returns remain unresolved. For example, Johnson et al. (2009) argue that the significant abnormal return spreads earned by strategies relying on these measures is a statistical artifact of ignoring industry clustering. That is, industry instead of governance is the source of variation in returns across these governance portfolios. Once statistical tests are properly adjusted for these industry effects, Johnson et al. (2009) find that the significance of the abnormal return spreads based on either the E or G measures is eliminated. Relatedly, Bebchuk et al. (2013) put forward a learning explanation for the reduced profitability of portfolios that load on these corporate governance measures and argue that while this profitability may be waning, the link between governance and firm performance has been stable over time. Furthermore, statistical inference when dealing with corporate governance measures based on takeover provisions is complicated by the fact that these metrics show limited time variation. This then makes it difficult to establish a causality link between corporate governance and firm performance because the effects of corporate governance cannot be separated from those of other time-invariant firm characteristics, such as, for example, a firm's culture.

In addition to these academic studies, numerous commercial corporate governance measures have also been introduced. Firms such as Risk Metrics/ISS, Governance Metrics International, and The Corporate Library have provided institutional investors with the ratings of the quality of firm governance. Given their greater access to data and potentially more sophisticated models, it would be expected that these commercial measures would perform favorably against simple count scores like the G or E measures. To the contrary, Daines et al.

(2010) find that the governance ratings of these commercial providers bear little empirical relation to either a firm's subsequent operating performance, the likelihood of shareholder litigation, or the probability of financial restatements. However, they find somewhat stronger predictive evidence for MSCI's AGR governance rating[1] that uses information on financial statements in addition to observable corporate governance measures such as board structure. In contrast to other commercial corporate governance measures, Daines et al. (2010) also find that AGR has modest ability to forecast excess stock returns, at least as of December 31, 2005. As argued by Daines et al. (2010), AGR views a firm's financials as an output of its governance. That is, poor corporate governance facilitates unreliable financial reporting by a firm's management. Therefore, a more accurate assessment of the effects of corporate governance may be formulated by taking into account both corporate governance outputs as well as inputs.

The purpose of this paper is to investigate the links between the quality of a firm's corporate governance as measured by its AGR score and its subsequent operating performance and stock price behavior. No systematic analysis of the AGR metric is available in the literature. To fill this void, we rely on an extensive database of AGR scores that ranks approximately 8,300 firms over the January 1997 to December 2011 sample period. This comprehensive panel data set affords us the opportunity to more carefully examine the links by which corporate governance impacts firm performance.

The AGR metric differs importantly from the G and E measures because a firm's AGR score exhibits non-trivial variation over time. For example, for the poorly governed firms that fall in the bottom 10% of the AGR distribution in a given month, only about 35%, on average, remain in this decile twelve months later. Similarly, about 40% of firms in the top 15% of AGR scores remain in this group after twelve months. We find little or no correlation between AGR scores and G and E measures. These findings confirm that AGR scores capture

[1]The AGR methodology was developed by Audit Integrity. In August 2014, MSCI acquired Governance Holdings Inc. which was formed by the merger of Audit Integrity, Governance Metrics International, and The Corporate Library. MSCI is now responsible for AGR ratings.

a dimension of governance that is distinct from that reflected by the number of anti-takeover provisions in place.

In light of this evidence, we ask whether corporate governance as captured by AGR is associated with higher future firm operating performance. We find that higher AGR-rated firms are indeed characterized by better future operating performance as measured by the firm's Return on Assets (ROA). In particular, a 10-point increase in AGR rating is accompanied by a 0.15% expected increase in that firm's 2-year ahead industry-adjusted ROA. A similar positive relation is found when relating the AGR score to other measures of a firm's output previously used in the literature such as Tobin's Q, net margin, and sales growth. In the cross-section, the effect is more pronounced for firms in the lower AGR decile, i.e. poorly managed firms. We also find that over time, the relation between AGR and operating performance is actually stronger in more recent years. Importantly, these results hold even after controlling for firm fixed effects and time-varying firm characteristics. While our tests cannot completely address the endogeneity of a firm's corporate governance structure, they increase the odds in favor of a causal link that runs from changes in a firm's governance to future profitability.

We also construct a portfolio that is long the stocks of better governed firms (i.e. Conservative, top 15% of AGR scores) and short the stocks of poorly governed firms (i.e. Very Aggressive, bottom 10% of AGR scores). We find that this portfolio delivers an abnormal return or alpha as large as 50 basis points per month when benchmarked against the 5-factor Fama and French (2014) model augmented by momentum as well as two accounting factors that load on the accrual and earnings surprise "anomalies". This result is robust to alternative portfolio formation strategies (value- versus equal-weighted, monthly versus annual rebalancing) and holds whether we use excess or industry-adjusted returns. Most of the profitability of this strategy originates with the portfolio of stocks having low AGR scores which delivers a negative and significant alpha of about 40 basis points. The significance of the loading on the AGR metric is further confirmed in Fama and MacBeth (1973) cross-sectional regressions that include a wide array of firm-level controls. Interestingly, we find that the premium for governance has been declining almost monotonically over time. This pattern is consistent with the learning argument of Bebchuk et al. (2013) who find that the alpha associated with trading strategies based on the G and E measures has been waning in recent years.

Overall, these findings suggest that firms with poor corporate governance as captured by a low AGR score tend to be subsequently characterized by abnormally low returns and poor operating performance. Since a low AGR score also reflects an increased likelihood of shareholder litigation and financial restatements, our paper also contributes to the recent literature on unethical corporate behavior. For example, Biggerstaff et al. (2015) document that CEOs who backdate their options are more likely to engage in corporate misbehavior and to induce an unethical corporate culture. This behavior eventually results in more value-destroying acquisitions, more extensive reliance on accounting manipulations, and lower stock returns. Corporate fraud and misbehavior may ultimately undermine investors' trust in financial markets and have an overall detrimental effect on stock market participation (Giannetti and Wang (2016)). We contribute to this discussion by showing that a firm's AGR score aggregates valuable warning signals and reliably allows investors to identify firms at risk of corporate fraud.

## 4.2 The AGR Metric

A firm's AGR score measures the overall risk that the firm engages in fraudulent or misleading accounting and governance activities. Using publicly available information, MSCI's objective is to discriminate between fraudulent and non-fraudulent firms. To do so, it ranks firms by their AGR scores and then groups them ranging from Very Aggressive (bottom 10%) to Conservative (top 15%), with the bulk of firms being classified as Aggressive (25%) or Average (50%).

Being proprietary, the exact algorithm by which a firm's AGR score is calculated is not publicly available. However, in general, the following five risk categories are considered: (*i*) corporate governance, (*ii*) high risk events, (*iii*) revenue recognition, (*iv*) expense recognition, and (*v*) asset-liability valuation. Within each of these risk categories, multiple issues (or "games") are tabulated. There can be as many as twenty-five issues per category. For example, issues within the revenue recognition category include high operating revenues, large accounts receivables, large inventory, and small unearned revenues. Each issue, in turn, is measured by one or more metrics. For example, corporate governance metrics include the percentage of board directors who are officers, incentive compensation over total compensation for both the firm's CEO and CFO, and the ratio of CFO to CEO total compensation.

These metrics are the fundamental ingredients of an AGR score. In particular, firms that exhibit extreme values in these measures are hypothesized to be of higher risk of fraudulent accounting and governance activities. To that end, each metric is examined for unusual behavior according to (i) an industry comparison (number of inter-quartile ranges from the industry median), (ii) it's one year change (percentage change from previous year), as well as (iii) it's volatility (variance over the previous eight quarters). *Only* if a firm's particular metric exhibits unusual behavior, defined to be in the corresponding extreme 20% of all observed values, is that metric included in a firm's AGR score.

A firm's AGR score is then constructed as a weighted average of its extreme metrics. The weight assigned to a particular extreme metric value is determined by its importance in detecting fraudulent behavior. In particular, this weight is given by the estimated odds ratio associated with whether extreme values of the metric explain particular examples of fraudulent behavior. The scores are then transformed to fit a curve with the above predefined percentile cutoffs corresponding from Very Aggressive, with a minimum AGR score of 1, to Conservative firms, with a maximum AGR score of 100.

## 4.3 Data and descriptive statistics

We rely on a comprehensive database of AGR scores that ranks approximately 8,300 firms during the January 1997 to December 2011 sample period. AGR scores are generally updated after the public release of new quarterly or yearly financial statements. Because of this, changes in AGR scores may occur at any point in calendar time. In our analyses, we rely on monthly observations and only update AGR scores at the end of the month following a score change. We apply this lag to ensure that our regression results are not subject to any potential look-ahead biases. Once a firm's AGR score is updated, we retain this score until when it is updated once again. We match our AGR dataset to the Center for Research in Security Prices (CRSP) dataset using a firm's CUSIP number. Balance sheet and other fundamental data are collected from COMPUSTAT.

The original sample consists of 611,838 firm-month observations. Following the literature, we apply a series of filters to these data. First, we retain only stocks with a CRSP share code equal to 10 or 11, thereby eliminating companies incorporated outside the US, trusts, closed-end funds, and REITs. Next, we remove dual-class shares owing to their peculiar governance structure (see Gompers et al. (2010)). Finally, we remove stocks with a price lower than $1 (''penny stocks''), and drop observations with a monthly return greater than 300% (16 observations) to avoid exceptionally high returns that may exert undue influence on our results. These filters leave us with a reference sample of 529,833 firm-month observations on 7,189 firms.

Next, we turn our attention to the time-series and cross-sectional characteristics of the AGR scores themselves. For each year in the sample period, Table 4.1 summarizes the distribution of AGR scores. After a few initial years, we see that both the number of observations as well as firms being followed remains stable. The distribution of AGR scores is also fairly stable over time, with median and mean AGR scores varying within the 45 to 54 range. The same observation applies to the 10th, 35th, and 85th percentiles that serve as cut-off points for AGR rankings from 'Conservative' to 'Very Aggressive'.

Johnson et al. (2009) point out that particular care must be paid to control for industry composition when investigating corporate governance. To offer a first glimpse into this issue, Figure 4.1 displays the average number (blue bars) and market capitalization (grey bars) of AGR-rated firms as a fraction of the CRSP universe for each of the 30 Fama and French industries. We see that each industry appears to be equally represented in our sample, with average market capitalization fractions ranging from a low of 0.56% (the residual industry) to a high of nearly 1% (''Tobacco Products''). In what follows, based on the findings of Johnson et al. (2009), we use the finer 3-digit SIC code to take into account industry clustering.

Table 4.2 examines the characteristics of the firms in our sample. In particular, the first set of rows report summary statistics for four measures of firm value and operating performance that have been related to corporate governance metrics in prior research, e.g. Daines et al. (2010) and Bebchuk et al. (2013). These include return on assets (ROA), Tobin's Q, net margin, and 3-year sales growth. All measures are industry-adjusted by subtracting the median value of the corresponding measure for all firms with non-missing COMPUSTAT data in the same industry in that fiscal year. The subsequent set of rows displays analogous statistics for the control variables that we use and that have also been relied upon in the prior literature: the market value of equity (Market Value); total assets (Assets); the ratio of capital expenditures to total assets (CAPEX/Assets); the debt-to-assets ratio (Leverage); and the ratio of R&D expenses to sales (R&D/Sales). The construction of these variables is detailed in the Appendix. For each year, we record all variables as of the fiscal year ending on or before December and match them to the firm's AGR score as of December of that year. Thus, a firm whose COMUSTAT last fiscal year entry for 2005 is recorded on May 2006 would be matched with its AGR score as of December 2005. We provide statistics for both levels and logs of equity and total assets as the log values will be used in our regressions to account for the high skewness of these variables.

At the median, the industry-adjusted characteristics of the firms in our sample are close to zero. This implies that AGR-rated firms are fairly representative of the universe of CRSP companies across each industry. The contemporaneous correlations of the firm performance measures with AGR, reported in the fourth column, indicate that highly rated firms tend to have, on average, a lower Tobin's Q, higher net margins, and to have experienced lower sales growth in the past three years. The correlations are, however, quite modest and never exceed 0.10 in absolute value. Turning to the controls, highly rated AGR firms appear to be significantly smaller in size, whether measured by equity or total asset value, and to be less levered.[2]

In our subsequent analyses, we report results using all AGR-rated firms as well as restricting attention to only those firms in the two extreme groupings, 'Conservative' and 'Very Aggressive'. For this reason, the last three columns of Table 4.2 report the average values of the performance measures and controls for these two groups and their differences. To properly account for potential time-series and cross-sectional correlations, statistical significance for the differences are based on doubly-clustered standard errors at both the year and firm level. The signs of the differences are consistent with the correlations reported across all firms. In particular, 'Conservative' firms tend to be characterized by higher net margins, lower sales growth in the prior 3 years, smaller size, and lower leverage. There is also some evidence, albeit economically more modest, that 'Conservative' firms have lower Tobin's Q. We note that the large difference in size is partly due to the impact of outliers. Median differences in Market Value and Assets appear less dramatic at $306 million and $363 million, respectively. Nevertheless, taken together, the evidence indicates that the two sets of firms appear *ex-ante* quite dissimilar. This suggests that including the controls in our analysis is key to ensuring that the AGR classification is not merely reflecting observables such as firm size.

The last two rows of Table 4.2 relate the AGR scores to the G and E measures. We focus on the data from the 1998, 2000, 2002, 2004, and 2006 Investor Responsibility Research Center (IRRC) publications that overlap with our sample period, and contrast the G and E

[2]These results are clearly not independent, as leverage is on average positively correlated with size.

measures with the last AGR score available for a firm in each of these years. The combined dataset consists of about 7,000 observations on about 2,400 firms. As a preliminary, we note that the mean (median) market capitalization of these firms is much larger, at about $7.5 billion ($1.5 billion), when compared to the corresponding results presented in Table 4.2. These values are comparable to those reported in Core et al. (2006) and highlight that corporate governance measures based on anti-takeover provisions tend to be available for larger firms. Turning to their correlations with corresponding AGR scores, they are nearly zero for the G score and slightly positive for the E index. This implies that the type of corporate governance information contained in AGR scores is distinct from that conveyed by indices based on anti-takeover provisions. If anything, firms in the 'Conservative' segment of AGR scores feature somewhat *higher* G and E measures as compared to the 'Very Aggressive', but the differences are not significant.

We next analyze the time-series properties of AGR scores. The top Panel of Table 4.3 reports the autocorrelation coefficients of AGR scores at the firm level at lags of 1, 2, 3, 6, and 12 months. AGR scores are characterized by significant time-variation, as can be gleaned by the 12-month autocorrelation of 0.47. This is in line with the 0.55 figure documented by Daines et al. (2010) when working with their 2005 AGR snapshot. Panel B of the Table presents persistence statistics across the AGR groups. We assign groups at the beginning of each month and then track the firms within each group (from "Very Aggressive"= 1 to "Conservative"= 4) in the subsequent 1, 2, 3, 6, and 12 months. We then compute the average group value, the average AGR score, and the fraction of firms that remains in the same group after each period (Retention %). We see that the ordering in AGR groups is preserved even after a year. However, we also observe a convergence toward the average, which is consistent with the above-documented autocorrelation in AGR scores. For the group of 'Very Aggressive' AGR firms, about 35% of firms remain in that group after a year. The same statistic is slightly higher at 41% for firms in the other extreme, 'Conservative'. Similar conclusions hold when focusing on AGR deciles rather than groups in Panel C of the Table.[3]

## 4.4 The AGR metric and Operating Performance

In this section, we correlate AGR scores to measures of firm value and operating performance. Our goal is to investigate whether corporate governance, as captured by a firm's AGR score, is a reliable predictor of future operating performance. A distinct feature of our estimation approach is that, given the documented time-variation in the AGR score of a given firm, we are able to include firm fixed effects in our regression framework. This is in contrast with much of the previous research that relies on corporate governance indices that exhibit little or no time variation.

### 4.4.1 Return on Assets (ROA)

We begin by analyzing the relation between AGR scores and ROA. In the corporate governance literature, this measure has been used by, among others, Core et al. (2006) and Daines et al. (2010). Under the hypothesis that good governance results in more value-enhancing decisions, we expect a positive relation between AGR scores and operating performance.

In Panel A of Table 4.4, we estimate pooled regressions of contemporaneous and future ROA on AGR scores. To capture the direct and indirect effects of governance, we investigate this relation both with and without including cross-sectional controls. As discussed above, ROA is industry-adjusted by its median value in the same three-digit SIC code industry. Future ROA is computed as the firm's ROA in fiscal year $t+2$, thereby avoiding any potential overlap with the timing of our dependent variables.[4] All regressions include both year and

[3]While AGR data are available beginning in 1996, ratings were first released to the public in October 2004. In light of a potential look-ahead bias, we test the relation between AGR and operating performance at an annual frequency using the full sample of data and test for robustness in the post-2004 data. For the return analysis, we restrict our attention to the post-2004 period to ensure that our results represent that of a truly implementable trading strategy.

[4]This implies that since a great majority of firms report financials in December of each year, we use the last available AGR score in, say, 2003 to predict ROA computed as of December 2005.

industry fixed effects and ROA is expressed in percentage terms.

Column (1) of Table 4.4 shows that, consistent with Table 4.2, the contemporaneous relation between AGR and ROA is slightly negative, but not statistically significant. After controlling for firm characteristics (column (2)), however, we see that AGR scores appear to be positively and significantly related to ROA. In the next two columns, we include firm fixed effects. This amounts to asking whether variation in AGR scores for the same firm correlates with variation in its ROA. The loading on AGR is now much smaller at 0.012, and is significant only at the 10% level. In sum, there is some evidence that firms with higher AGR scores display better current performance than otherwise comparable firms.[5]

In columns (5)-(8) of Table 4.4, the dependent variable is now future ROA. Here the results indicate that AGR scores represent a reliable predictor of future firm profitability. The loadings are 0.011 (no controls) and 0.030 (with controls) when excluding firm fixed effects, both significant at the 1% level. The significance and magnitude of this relation are preserved when including firm fixed effects, implying that time-series variation in AGR scores for the same firm is indeed capturing future operating performance. To put these numbers in perspective, the 0.015 estimate in column (4) implies that a one-standard deviation increase in AGR, which is about 28 from Table 4.1, is associated with an expected increase in the firm's future ROA of about 0.42%.

In the bottom Panel of Table 4.4, we present estimates in analogous regressions where now the AGR score is replaced by dummies for firms in the "Aggressive", "Average", and "Conservative" groups of AGR scores. For contemporaneous ROA, we see that the relation with these AGR groups is not clear. For example, it is humped in specifications (1) and (4), increasing in specification (2), and decreasing in specification (3). This is in contrast with columns (5)-(8), where the loadings on AGR groups are monotonically increasing. From the estimates in column (6) that include time and industry fixed effects, we see that better

[5] The reduction in the number of observations (Obs.) when adding controls other than AGR is mainly due to R&D/Sales being often missing. When excluding R&D/Sales, the number of observations in specification (8) increases to 30,200, and the loading on AGR is smaller at 0.008 but again statistically significant ($t$-ratio of 2.03). Given the significance of R&D/Sales, we decided against excluding it from the set of regressors.

firm governance is accompanied by improved ROA in the three groups of 0.241%, 1.247%, and 2.376%, respectively. A similar pattern is observed when including firm fixed effects, although the estimates are generally lower and are significant only for the 'Conservative' group.

### 4.4.2 Other operating performance measures

It is natural to ask whether the association between AGR scores and operating performance is restricted to ROA as a measure of firm performance. To address this question, we follow prior research that looks at whether governance metrics are useful determinants of future firm value (Tobin's Q), financial profitability (Net Margin), and operating growth (3-year sales growth).

Panel A of Table 4.5 presents the corresponding estimates for the specifications that include time, industry, and firm fixed effects. When entering alone as a predictor, we see that high AGR scores are associated with higher Tobin's Q, higher net margin, and higher sales growth. The point estimates are 0.117, 0.049, and 0.056, respectively, and all are significant at the 5% level or better. When conditioning on our set of controls, however, the significance is preserved only for Net Margin, while for the other two measures the relations become insignificant (and negative in the case of sales growth). Overall, the evidence that AGR scores also reliably predict other dimensions of a firm' performance is indicative that the link between corporate governance and firm output is rather robust.

### 4.4.3 Additional analyses

We also conduct additional analyses to investigate the stability of our findings with respect to various dimensions of our dataset. In particular, we check whether our results are sensitive to the definition of the AGR groups by relying on AGR score deciles to form groups. We also work on sub-samples by excluding firms in the ''Very Aggressive'' group. Finally, we test for time-variation in these effects by introducing separate dummies for the pre- and post-2003 periods. The results for the predictive regressions of the four dependent variables on AGR with year and firm fixed effects are presented in Table 4.6. Overall, we find reliable evidence that AGR scores are related to future operating performance.

#### 4.4.3.1 Deciles

Akin to the standard portfolio formation approach, we investigate the dependence between operating performance measures and AGR deciles, instead of the ratings *per se*. Working with deciles may increase the power of the tests while making identification stronger as the inclusion of firm fixed effects effectively restricts the sample to firms whose AGR decile changes over time. Results are reported in Panel A of Table 4.6. We see that AGR is an economically and statistically robust predictor of future performance, irrespective of how the latter is measured. For example, a one-decile increase in AGR is associated with a 0.55% increase in 2-year ahead sales growth.

#### 4.4.3.2 Excluding low AGR firms

We test to what extent the results are driven by firms in the very low, i.e. tenth decile (D1) of AGR scores. In Panel B of Table 4.6, we repeat our analysis relating future performance to AGR scores while excluding firms in D1. The results show that AGR continues to predict future performance, although the statistical significance and the magnitude of the effects are weaker than compared to the evidence in Tables 4.4 and 4.5. From these results, we conclude then that AGR is a particularly valuable predictor for firms with weak corporate governance that are more prone to management misconduct. However, our evidence does not appear to be confined only to these firms in particular.

#### 4.4.3.3 Subsample results

Finally, we investigate the time-variation in AGR predictability by estimating the operating performance regressions but including a separate interaction term of the AGR score with a pre- versus post-2003 dummy. The bottom panel of the Table indicates that the relation between AGR scores and firm performance is not confined to the 1997-2003 period. If anything, the relation is stronger in the latter subsample as the coefficient remains significant across all four operating performance measures (as opposed to the pre-2003 period, where it is insignificant in the case of 3-Year Sales Growth). Since AGR ratings became available to subscribers starting only in October 2003, these results also reassure us that our conclusions are not spuriously arising from any look-ahead bias in the dataset.

## 4.5 Stock returns and AGR scores

We next investigate whether corporate governance, as measured by AGR, is priced in stock returns. Initial but limited work by Daines et al. (2010) suggests that a significant spread can be earned by going long well governed (high AGR) firms and shorting poorly governed ones (low AGR). The panel nature of our dataset allows us to investigate the returns obtained when loading on AGR over an extended period of time. In particular, as firms' AGR scores change over time, our analysis will be able to isolate the extent to which stock returns' react to changes in governance as opposed to company-specific attributes that otherwise cannot be controlled for with a single snapshot view of governance.

### 4.5.1 Portfolio performance regressions

We first analyze the performance of AGR-sorted portfolios. The portfolio formation is in the spirit of Fama and French (1993) and Hirshleifer et al. (2012). As mentioned previously, for this analysis we restrict our attention to the post-2004 period to ensure that our results represent that of an implementable trading strategy. Specifically, at the end of each month starting in January 2005, we group firms into thirds based on their end-of-month market capitalization (from Small to Large) and, separately, by the four AGR groups (from Very Aggressive to Conservative). The intersection of these size and AGR groups yields twelve portfolios, ranging from S&VA (Small & Very Aggressive) to L&C (Large & Conservative). We compute each corresponding portfolio return in the subsequent month as, alternatively, the value-weighted (VW) or equal-weighted (EW) average returns to stocks within the portfolio, where the weights in the former case equal the relative market capitalization of a firm's stock as of the formation date. The portfolios are subsequently rebalanced every month. We construct returns to a given AGR group as the simple average across portfolios with different sizes.[6] Similarly to Gompers et al. (2003a) and Bebchuk et al. (2009), we also investigate the performance of a portfolio that is long better governed, high AGR stocks (Conservative) and short stocks in the bottom AGR group (Very Aggressive), $AGR_p =$ (S&C+M&C+L&C)/3 - (S&VA+M&VA+L&VA)/3.

To assess whether AGR-based portfolios produce average returns that cannot be attributed to exposure to well-known risk factors, we rely on the following performance attribution model:

$$
\begin{aligned}
r_{p,t} \quad = \quad & \alpha + \beta_1 \mathrm{RMRF}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{UMD}_t + \\
& \beta_5 \mathrm{RMW} + \beta_6 \mathrm{CMA} + \beta_7 \mathrm{ACC}_t + \beta_8 \mathrm{SUE}_t + \epsilon_{p,t}
\end{aligned}
\tag{4.1}
$$

where $r_{p,t}$ is the return to a given AGR-sorted portfolio, $p = \{Very\, Agg, Agg, Avg, Cons\}$, in excess of the 3-month T-Bill rate. The first four regressors are the standard Fama and French (1993) factors measuring zero-investment returns for exposure to market risk (RMRF), size (SMB), and book-to-market ratio (HML), plus the momentum portfolio UMD as constructed by Fama and French (1996). This is the benchmark model used in prior studies that investigate the performance of governance-sorted portfolios. Given the nature of AGR, however, we augment this list with four additional factors capturing trading strategies (risk factors) that are either related to operating performance or based on accounting information. The first two additional factors, RMW and CMA, have been recently proposed by Fama and

[6] So, for example, the Very Aggressive portfolio is constructed as (S&VA+M&VA+L&VA)/3.

French (2014) based on the evidence that profitability and investment have a significant role in explaining the cross-section of expected returns. RWA is constructed as the difference between the returns on diversified portfolios of stocks with robust and weak profitability. CMA is defined as the difference between the returns on diversified portfolios of the stocks of low and high investment firms. The final two factors are the accrual factor (ACC) of Hirshleifer et al. (2012), constructed as the return difference to portfolios of stocks with low versus high accruals, and a portfolio based on standardized earning surprises (SUE). By including these two additional factors, we attempt to differentiate the corporate governance information contained in AGR from exposure to previously documented accounting-based "anomalies".[7]

Panel A of Table 4.7 presents the OLS estimates of the time-series regression, equation (4.1), for portfolios ranging from Very Aggressive to Conservative as well as for the $AGR_p$ portfolio that is long Conservative firms and short Very Aggressive firms. The left-hand side of the Table is based on value-weighted returns, while the right-hand side is based on equal-weighted returns. As can be seen, the unexplained average monthly return or *Alpha* for the value-weighted Very Aggressive group is -0.451% and is significant at the 1% level. For the equal-weighted Very Aggressive portfolio, its *Alpha* is slightly lower at -0.337% but still significant at the 5% level. Thus, firms in the low AGR group deliver significant average risk-adjusted returns. High AGR firms also tend to outperform the benchmark model. However, the corresponding *Alpha* is quite small in absolute value, ranging from 0.090% (Conservative in the value-weighted case with a $t$-stat of 1.26) to 0.179% (Conservative in the equal-weighted case with a $t$-stat of 2.51). Taken together, the spread between Conservative and Very Aggressive firms for both value-weighted and equal-weighted portfolios is approximately 50 bps per month and is highly significant. This spread originates primarily from the group of Very Aggressive firms suggesting that the AGR score is particularly able to identify poorly managed firms. It is also noteworthy that this spread is greater when portfolio returns are

[7]The ACC and SUE factors are characterized by the highest monthly Sharpe Ratio of 0.17 and 0.10, respectively, during our sample period. This too underlines the importance of including them in the analysis.

computed in value-weighted rather than equal-weighted terms, and so is not the result of loading on smaller, and potentially more difficult to short shares.

Looking across risk exposures, we see that Very Aggressive firms load significantly and positively on the market, size, and book-to-market ratio risk factors. Interestingly, the Very Aggressive portfolio loads negatively on the momentum and RMW factors, confirming the view that these firms have recently experienced negative returns and suffered weak profitability. Across all portfolios and specifications, we find very limited exposures to the two accounting factors, the sole exception being the value-weighted Conservative portfolio with a -0.065 loading on the earnings surprise factor, albeit only marginally significant with a $t$-statistic of -1.71. In addition, Conservative firms appear to load only on the market and book-to-market ratio factors. The returns of the $AGR_p$ portfolio that goes long Conservative firms while shorting Very Aggressive firms are only weakly related to the Fama and French (1993) factors but load positively and significantly on momentum and negatively but not significantly on the SUE factor.

In Panel B of the Table, we repeat this empirical analysis but now using industry-adjusted returns. Industry-adjusted returns are obtained by subtracting from each stock return its corresponding value-weighted three-digit SIC code industry return. Accounting for this industry effect now increases the AGR spread to 68 bps (value-weighted) and 71 bps (equal-weighted). As before, the large bulk of this spread is attributable to low AGR firms underperforming with respect to their peers. Interestingly, industry-adjusted *Alpha*s are now monotonically increasing across AGR groups. Overall, the significance of the risk factor exposures is similar to that documented in Panel A.

In addition to industry adjustment, we also investigate whether this unexplained return originates in specific industries. To that end, Figure 4.2 displays our estimates for *Alpha* when stocks from a given Fama and French industry are removed from the original sample. Notice that the numbers vary within a rather narrow range, from 0.525% (when excluding "Personal and Business Services") to 0.749% (when excluding "Business Equipment"), and are all highly statistically significant. These results confirm that the spread attributable to AGR is broad based and not particular to a specific industry.

In sum, the strategy of going long firms with high AGR scores while shorting firms with low AGR scores delivers a positive return even after adjusting for an extensive set of risk factors. These results are consistent with AGR capturing an important dimension of the effectiveness of corporate governance that is not fully reflected in contemporaneous stock valuations.

### 4.5.2 Fama and MacBeth regressions

As an alternative to AGR-sorted portfolios, we further evaluate the robustness of our findings by estimating monthly firm-level regressions using the approach of Fama and MacBeth (1973). This cross-sectional framework has the benefit of allowing the inclusion of a relatively large number of firm characteristics that is impractical to do in the time-series portfolio approach. We find that AGR's economic and statistical significance persists even when accounting for these additional dimensions of risk.

Specifically, each month $t$ from January, 2005 to December, 2011 we estimate the following cross-sectional model:

$$r_{i,t+1} = \gamma_{0,t} + \gamma'_{1,t}\mathbf{X}_{i,t} + \epsilon_{i,t+1} \tag{4.2}$$

where $r_{i,t+1}$ is the return to stock $i$ at the end of month $t+1$, and $\mathbf{X}_{i,t}$ is a collection of firm-specific control variables that are observed at the end of month $t$. The average coefficient, $\overline{\gamma}'_1 = 1/T\sum_t \gamma'_{1,t}$, measures the expected return (risk premium) to a zero-cost portfolio that loads on a given characteristic. Our interest is in the premium for AGR. Since AGR scores are hypothesized to be increasing in the effectiveness of governance, we expect a positive estimate of this premium reflecting positive returns to better governed firms. The comprehensive list of the conditioning variables in $\mathbf{X}_{i,t}$ follows from Hirshleifer et al. (2012), and is based on evidence in the prior asset pricing and accounting literatures. These controls include the market beta ($\beta$) estimated on the prior 60-month period; log market capitalization; log book-to-market ratio; the stock return in month $t$ (*Ret(t)*) and the cumulative return in months $t-12$ through $t-1$ (*Ret(t-12:t-1)*); idiosyncratic volatility ($iv$), as measured by the square root of average squared residuals from a 3-factor Fama and French (1993) model estimated using daily returns in month $t$, following Ang et al. (2006); the value of the accrual $Accrual$, computed as in Hirshleifer et al. (2012); and the most recent standardized earning surprise, *SUE*. In order to maintain comparability of the results across specifications, we restrict the sample to firms with at least 60 months of available return data.

Table 4.8 reports the average coefficients for the regression (4.2), along with their corresponding time-series $t$-statistics. Five different specifications of $\mathbf{X}_{i,t}$ are explored. In the first column, the AGR score enters alone as a determinant. The corresponding coefficient is positive at 0.006, and is strongly significant with a $t$-statistic of 2.93. In the second column, we add a first set of control variables. The coefficient on AGR is now slightly lower at 0.005, but with a larger $t$-statistic of 4.11. For the other regressors, we note that the weak relation between expected returns and market betas and book-to-market is consistent with Boyer et al. (2010). In specification (3), we see that the coefficient on AGR remains stable at 0.005 when including Accrual and earning surprises.

Finally, we run a kitchen-sink regression in which we include all controls first excluding (column (4)), and then including (column (5)) the AGR score. In this specification, the loading on AGR remains positive at 0.005 and is significant at the 1% level with a $t$-statistic of 3.86. Among other factors, momentum and accrual stand out as the most robust predictors. The statistical significance of AGR goes hand in hand with its economic significance. The 0.005% monthly premium in Table 4.8 implies that an average difference of 83 points between the Very Aggressive and Conservative groups (from Table 4.3) translates into a monthly average return differential of 0.415%, or about 5% annually.

### 4.5.3 Time-series variation in AGR premium

From an asset pricing perspective, the fact that well governed firms persistently deliver higher risk-adjusted returns than poorly governed firms is puzzling. If differences between firms' future governance, and hence performance, are already incorporated in current valuations, it should not be possible to generate abnormal profits by trading on governance metrics.

A possible explanation for the documented profitability of our AGR trading strategy is that it reflects a slow adjustment towards equilibrium expected returns. As argued by Bebchuk et al. (2013), if this is the case, we should detect a decline in abnormal returns as market participants begin to more aggressively trade on AGR even as we have observed that the relation between AGR and firm operating performance has actually become stronger with time. To investigate this possibility, we explore the time variation in the AGR premium. Specifically, Figure 4.3 displays the 24-month trailing average of the slope of the AGR metric from the full specification of the Fama-MacBeth regression (column 5 of Table 4.8). The plot reveals a distinct downward trend in the premium. From a peak of approximately 80 basis points (monthly) during the 2005 to 2006 time period, the premium declines almost monotonically and actually turns negative in 2009 before returning to zero by the end of the sample. Thus it appears that the declining profitability of corporate governance-based trading strategies, first evidenced by Bebchuk et al. (2013), also extends to the AGR score.

## 4.6 Credit risks and AGR scores

We also investigate the effect of corporate governance on changes in a firm's cost of debt, as measured by its yield spreads and credit rating. In addition, we study the impact of corporate governance on a firm's credit risk, as captured by its CDS spreads.

### 4.6.1 Data and methodology

In order to measure firm-level credit risk, we use CDS quotes from Markit, which has become the standard source for academic research.[8] A CDS contract represents insurance against the default of an entity. The payment of a CDS contract represents the CDS premium and is stated as a percentage of the value of the contract. Thus, CDS spreads provide a direct measure of the credit risk for the underlying entity. In addition, recent empirical evidence asserts that CDS spreads are an effective and more timely measure of credit risk of an entity compared to the bond or stock market indicators (see, e.g., Jorion and Zhang, 2007; Blanco et al., 2005; Zhu, 2006). The monthly CDS data set ranges from January 2001 to December 2011. I use monthly spreads for five-year, USD-denominated, senior tier CDS contracts with the modified restructuring (MR) clause, as those type of contracts are the largest and most liquid.[9] In addition to CDS quotes, Markit also provides information about sector, country and region classifications for the underlying firms.

Firm credit ratings are the long-term issuer credit ratings compiled by Standard&Poor's over the period 1997-2011. The ratings range from AAA (highest rating) to D (lowest rating—debt in payment default). These ratings reflect S&P's assessment of the creditworthiness of the obligor with respect to its senior debt obligations. S&P classifies ratings below BBB as speculative. For purposes of our analysis, the multiple ratings are collapsed into seven categories following Ashbaugh-Skaife et al. (2006). See Ashbaugh-Skaife et al. (2006) for more details. To test the predicted relations between corporate governance attributes and credit ratings, we estimate an ordered logit model. We use ordered logit because the seven categories of credit ratings convey ordinal risk assessments; we can rank order firms' preferences across the rating categories but cannot assume uniform differences in benefits (costs) between the categories.

We obtain daily bond pricing information from TRACE over the period 2002-2011. We

[8] Markit obtains contributed CDS data from market makers' official books and records, which undergo rigorous data cleaning to guarantee that only the highest quality data is used in forming composite quotes. We use the five-year CDS spreads since they are the most liquid contracts and form over 85% of the whole CDS market (Jorion and Zhang, 2007).

[9] For more information about the documentation clauses, see ISDA Credit Derivatives Definitions published in February 2003.

follow the data cleaning procedure of Bessembinder et al. (2008) to eliminate canceled, commissioned, and corrected trades. We then obtain bond characteristics information (callable, convertible, fixed coupon, etc.) from Mergent Fixed Income Securities Database (FISD). Following Jostova et al. (2013), we eliminate preferred shares, non-US dollar denominated bonds, bonds with unusual coupons, bonds with warrants, bonds that are mortgage-or asset-backed, bonds that are convertible or are part of unit deals (i.e., features that would result in differential pricing).

We compute firm-level yield spreads following Klock et al. (2005). More specifically, our dependent variable, yield spread, is measured as the difference between the weighted-average yield to maturity on the firm's bond and the yield to maturity on a Treasury security with a corresponding duration, where the weight of each debt issue is the fraction of amount outstanding for that issue divided by the total market value of all outstanding traded debt for the firm. The yield on a corporate debt security is defined as the discount rate that equates the present value of the future cash flows to the security price. Control Variables include security-specific variables (credit ratings, duration, and bond age) and firm characteristics (leverage, profit margin (ROA), size, and stock volatility).

We compute security-level yield spreads following Cremers et al. (2007) and Bhojraj and Sengupta (2003). The yield defined as yield to maturity on debt issues minus yield to maturity on a U.S. Treasury bond of similar maturity. Control variables include issue characteristics (such as issue size, number of years to maturity, dummies for callability, senior and senior-secured debt, duration, and credit ratings) and issuer characteristics (leverage, ROA, size, stock volatility).

Appendix 4.A provides a detailed description of the variables used in this study.

### 4.6.2 Results

We use credit rating as a measure of a firm's cost of debt capital, which prior studies find is affected by the quality of firm governance. Following the literature, we use ordered logistic regressions to estimate the relationship between corporate governance ratings and future credit ratings issued by Standard and Poor's, after controlling for a number of variables shown to be related to credit ratings in prior research (see, e.g., Ashbaugh-Skaife et al., 2006). We find that better corporate governance (high AGR ratings) is positively associated with credit ratings (Table 4.12).

We also find that firms with higher AGR ratings have lower levels of credit spreads, as captured by their CDS spreads (Table 4.9 and 4.10) and bond yield spreads (Table 4.13 and 4.14). Thus, these findings show that AGR ratings are able to predict the subsequent changes in a firm's cost of debt and credit risk. These findings are related to AGR's rating of accounting practices (which are probably best viewed as governance outputs rather than as measures of governance inputs).

To the extent that the perceived lack of transparency could signal hidden bad news about a company, the quality of accounting information could have an impact on its cost of debt or offering yields. Indeed, lenders consider a firm's disclosures quality in their default risk estimation. Creditors use financial reporting and disclosure to assess firm health and viability. Managers may have incentives to issue misleading financial statements to conceal negative news and thereby provide private personal benefits or potential shareholder benefits. A policy of timely and detailed disclosures reduced lenders' and underwriters' perception of default risk for the disclosing firm, reduced its cost of debt (Sengupta, 1998). Additionally, Bhojraj and Sengupta (2003) argue that governance mechanisms can reduce default risk by mitigating agency costs and monitoring managerial performance, and by reducing information asymmetry between the firm and the lenders. Thus, governance mechanism can influence the assessment of default likelihood in agency risk and information risk dimensions. Moreover, an effective corporate governance mechanism can affect credit spreads and ratings through its impact on the default risk of the firm. Indeed, effective corporate governance can reduce agency risk and information risk. Information risk refers to the risk that firm managers have private information that would adversely affect the default of the loan. In addition, information risk indicates uncertainty about the true value of the firm. Governance mechanism can help reduce information risk by inducing firms to disclose information in a timely manner.

When we use G_score-Gompers et al. (2003b) as a measure of corporate governance, we find consistent results with Ashbaugh-Skaife et al. (2006), Cremers et al. (2007) and Klock et al. (2005). Results in Table 4.11 indicate that that high G-index (weak corporate governance or high takeover defense) is negatively associated with CDS spreads. Recall that a higher G_score indicates lower shareholder rights and greater management power. Thus, the smaller the G_score, the stronger the shareholder rights. Our results suggest that stronger shareholder rights are associated with lower firm credit ratings. Ashbaugh-Skaife et al. (2006) argue that the positive relation between credit rating and G-index is consistent with a "wealth redistribution" hypothesis that posits that bondholders may suffer potential wealth transfer effects associated with stronger shareholder rights. That is, from the bondholders' perspective, the risks of wealth transfer that can result with stronger shareholder rights outweigh the positive firm value effects documented in (Gompers et al., 2003b).

## 4.7 Conclusions

Does the market reward well governed firms? How can we identify these well governed firms? Several academic papers have relied on anti-takeover provisions and other governance inputs to identify weakly governed firms. Johnson et al. (2009) find that while the G and E measures have some correlation with poor operating performance and low Tobin Q values, they do not generate excess returns when industry clustering is accounted for. Similarly, commercial governance rankings have largely struggled in spite of their much better datasets and sophisticated models.

This paper focuses on MSCI's AGR governance rating that, unlike other governance ratings, relies on both governance inputs as well as outputs. We document that over the 1997-2011 sample period, a firm's AGR rating is economically and statistically related to future operating performance as measured by either ROA, sales growth, Tobin's Q, or net margin. The rating is especially valuable in tracking the performance of firms in the bottom AGR decile, that is, firms with poor corporate governance. In addition to operating performance, we investigate whether loading on AGR ratings generates abnormal stock returns. We document that a long-short portfolio that goes long better governed firms while shorting poorly governed ones delivers approximately a 5% risk-adjusted return even after controlling for an extensive set of risk factors. However, consistent with learning by the market, this abnormal performance has been declining over time. Taken together, our results confirm that corporate governance does systematically affect a firm's operating performance and its stock price behavior.

**Figure 4.1: Industry concentration of AGR-rated companies**

The figure reports the percentage of AGR rated firms within the 30 Fama and French industries computed as a fraction of the universe of CRSP stocks in each industry.

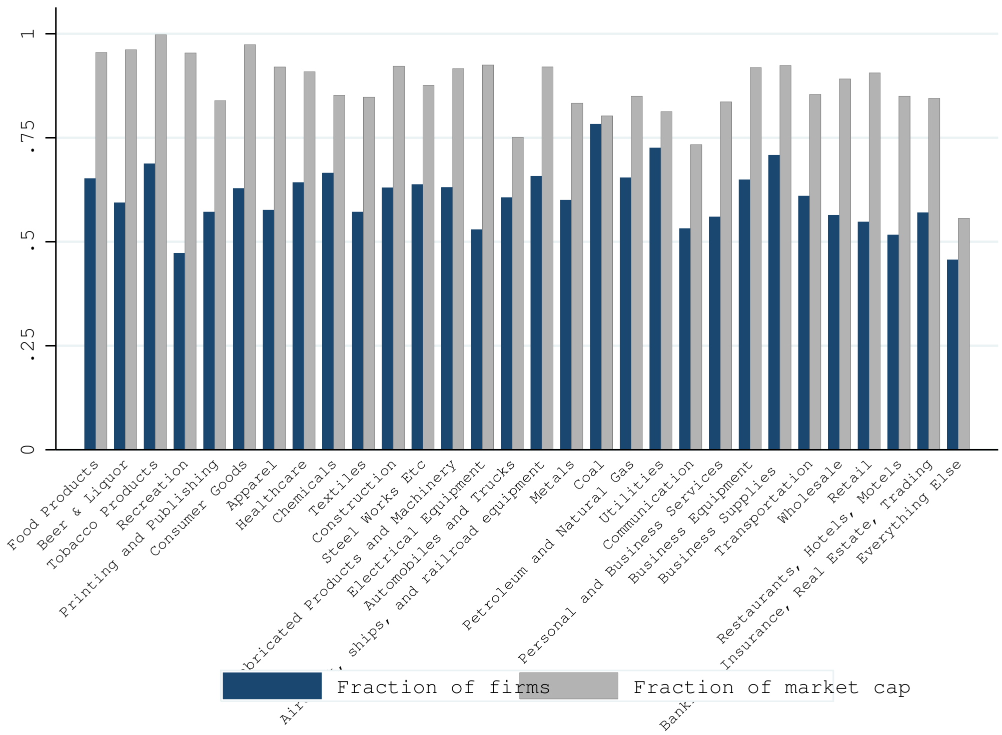


**Figure 4.2: Performance regressions and industry concentration**

The grey bars (left Y-axis) are the *Alpha* to the AGR factor (Conservative minus Very Aggressive) using the factor model of Table 4.7, when firms from the corresponding industry in the X-axis have been removed from the original sample. The grey bars (right Y-axis) are the corresponding $t$-statistics. The sample period is January 2005 to December 2011.

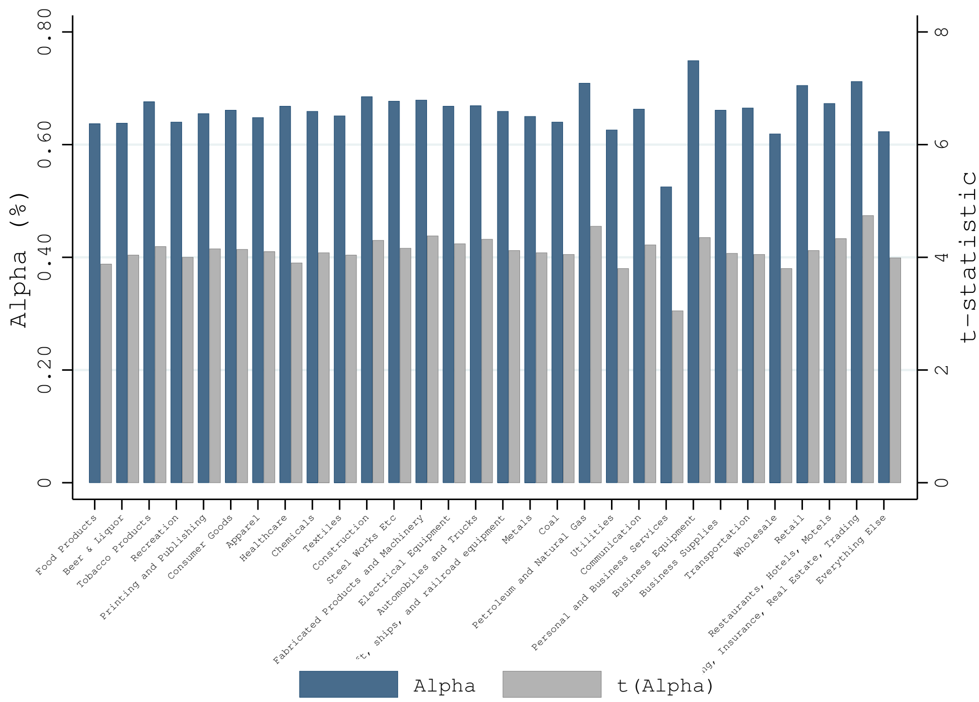


**Figure 4.3: Time variation in AGR premium**

We estimate monthly OLS Fama-MacBeth cross-sectional regression of stock returns of the AGR metric and firm-level controls, using the model in column 5 of Table 4.8. The Figure displays the trailing 24-month average of the slope on the AGR metric. The sample period is January 2005 to December 2011.

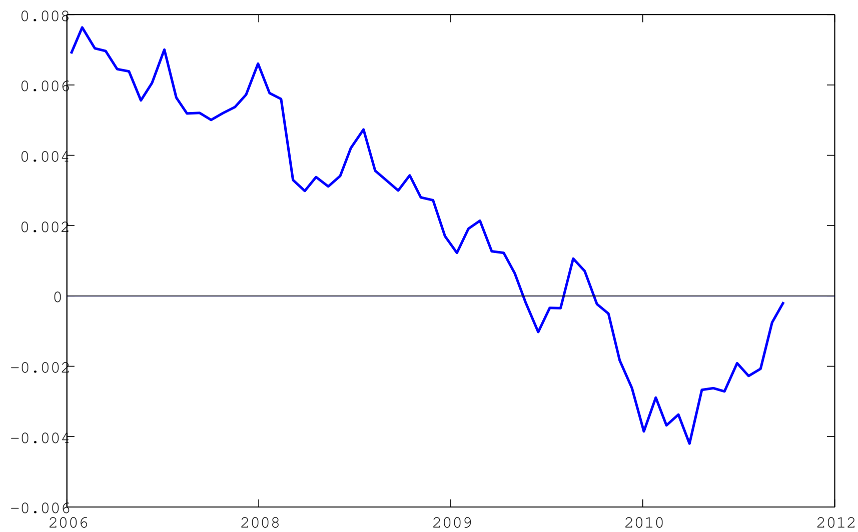


**Table 4.1: Descriptive statistics of AGR scores by year**

We provide the following summary statistics for the annual distribution of AGR scores over our sample period January 1997 to December 2011: mean; standard deviation; minimum; 10th, 35th, 50th (Median), and 85th percentiles; maximum; number of firm-month observations; and number of firms (permnos).

| Year | Mean | Median | Std Dev | Min | p10 | p35 | p85 | Max | Obs. | # of Firms |
|---|---|---|---|---|---|---|---|---|---|---|
| 1997 | 52.76 | 54 | 27.17 | 1 | 14 | 41 | 85 | 99 | 22,321 | 2,494 |
| 1998 | 53.78 | 55 | 27.41 | 1 | 15 | 41 | 85 | 99 | 28,678 | 3,010 |
| 1999 | 51.96 | 53 | 27.25 | 1 | 14 | 38 | 84 | 99 | 31,820 | 3,181 |
| 2000 | 48.12 | 47 | 27.09 | 1 | 11 | 34 | 81 | 99 | 33,384 | 3,380 |
| 2001 | 47.00 | 46 | 26.94 | 1 | 11 | 33 | 80 | 99 | 33,973 | 3,348 |
| 2002 | 46.62 | 45 | 26.77 | 1 | 11 | 32 | 79 | 99 | 35,271 | 3,373 |
| 2003 | 46.56 | 46 | 26.60 | 1 | 10 | 32 | 78 | 99 | 36,995 | 3,403 |
| 2004 | 47.02 | 46 | 26.73 | 1 | 11 | 33 | 79 | 99 | 39,484 | 3,628 |
| 2005 | 48.26 | 49 | 26.57 | 1 | 12 | 34 | 80 | 99 | 40,163 | 3,673 |
| 2006 | 48.33 | 49 | 26.62 | 1 | 12 | 35 | 81 | 99 | 40,633 | 3,739 |
| 2007 | 48.58 | 48 | 27.28 | 1 | 11 | 34 | 81 | 99 | 40,836 | 3,789 |
| 2008 | 47.25 | 47 | 27.10 | 1 | 11 | 33 | 81 | 99 | 37,251 | 3,548 |
| 2009 | 47.42 | 46 | 27.88 | 1 | 10 | 33 | 81 | 99 | 32,110 | 3,048 |
| 2010 | 50.99 | 51 | 28.13 | 1 | 11 | 37 | 85 | 100 | 36,324 | 3,711 |
| 2011 | 52.02 | 53 | 28.10 | 1 | 12 | 38 | 85 | 100 | 40,590 | 3,668 |

### Table 4.2: Summary statistics of characteristics of AGR-rated firms

We provide the following summary statistics for characteristics of AGR-rated firms measured at year end: the number of firm-year observations for a characteristic; mean value of a characteristic; median value of a characteristic; the Pearson correlation of a characteristic with the firm's last AGR score available that year; the mean value of a characteristic for Conservative firms whose AGR score ranked in the top 15% of AGR scores that year; the mean value of a characteristic for Very Aggressive firms whose AGR scores ranked in the bottom 10% of AGR scores that year; the difference in mean values between characteristics of Conservative and Very Aggressive firms. See the Appendix for the definition of the variables. For the G score and E Index, the summary statistics are based on values observed in the years 1998, 2000, 2002, 2004, and 2006. For the other variables, the sample period is 1997 to 2011.

| | Obs. | Mean | Median | Corr. with AGR | Mean Conservative | Mean Very Aggressive | Difference |
|---|---|---|---|---|---|---|---|
| ROA, Ind. Adj. | 48,139 | 0.005 | 0.004 | -0.002 | -0.002 | -0.007 | 0.008 |
| Tobin's Q, Ind. Adj. | 42,497 | 0.448 | 0.052 | -0.040 | 0.345 | 0.477 | -0.107* |
| Net margin, Ind. Adj. | 48,001 | -0.154 | 0.006 | 0.074 | -0.088 | -0.339 | 0.257*** |
| 3-Year Sales growth | 39,285 | 0.245 | 0.003 | -0.087 | 0.135 | 0.438 | -0.303*** |
| | | | | | | | |
| Market Value (in millions of $) | 48,320 | 3,601 | 423.135 | -0.126 | 1,181 | 8,877 | -7,688*** |
| Log(Market Value) | 48,320 | 6.233 | 6.048 | -0.172 | 5.714 | 6.626 | -0.892*** |
| Assets (in millions of $) | 48,352 | 6,984 | 615.498 | -0.099 | 2,398 | 26,397 | -24,053*** |
| Log(Assets) | 48,352 | 6.506 | 6.422 | -0.135 | 6.155 | 6.932 | -0.769*** |
| CAPEX/Assets | 45,600 | 0.050 | 0.031 | 0.014 | 0.049 | 0.046 | 0.003* |
| Leverage | 46,244 | 0.188 | 0.129 | -0.055 | 0.163 | 0.206 | -0.044*** |
| R&D/Sales | 24,384 | 4.923 | 0.049 | -0.007 | 2.590 | 16.247 | -13.642 |
| | | | | | | | |
| G Score | 7,002 | 9.192 | 9.000 | -0.002 | 9.142 | 9.067 | 0.075 |
| E Index | 7,002 | 2.416 | 2.000 | 0.015 | 2.510 | 2.416 | 0.095 |

## Table 4.3: Persistence in AGR scores

We tabulate the persistence of AGR scores (Panel A), AGR groups (Panel B), and AGR deciles (Panel C). At the beginning of each month, firms are grouped into deciles based on their AGR score reported at the end of the prior month. For each decile, from lowest (D1) to highest (D10), we report the average AGR score and the equal-weighted average return (in percentage) computed in the formation month M. We then track the firms in each decile in the subsequent 1, 2, 3, 6, and 12 months and compute the corresponding average AGR score, the equal-weighted average return (in percentage), and the fraction of stocks that remains in the decile (Retention %). The sample period is January 1997 to December 2011.

Panel A: AGR scores

| | Statistic | M | M+1 | M+2 | M+3 | M+6 | M+12 |
|---|---|---|---|---|---|---|---|
| AGR score | Autocorr. | 1.00 | 0.93 | 0.86 | 0.79 | 0.66 | 0.47 |

Panel B: AGR groups

| Group | Statistic | M | M+1 | M+2 | M+3 | M+6 | M+12 |
|---|---|---|---|---|---|---|---|
| | Group | 1.00 | 1.17 | 1.31 | 1.44 | 1.67 | 1.99 |
| Very Aggressive | AGR | 6.61 | 9.12 | 11.42 | 13.53 | 18.44 | 26.37 |
| | Retention % | 100 | 86.48 | 74.84 | 64.84 | 50.18 | 34.66 |
| | Group | 2.00 | 2.07 | 2.14 | 2.20 | 2.30 | 2.42 |
| Aggressive | AGR | 23.46 | 25.72 | 27.80 | 29.68 | 33.34 | 38.22 |
| | Retention % | 100 | 84.25 | 70.76 | 59.41 | 46.17 | 36.61 |
| | Group | 3.00 | 2.98 | 2.95 | 2.94 | 2.90 | 2.84 |
| Average | AGR | 57.08 | 56.48 | 55.91 | 55.39 | 54.29 | 52.45 |
| | Retention % | 100 | 90.43 | 82.23 | 75.22 | 65.97 | 58.42 |
| | Group | 4.00 | 3.86 | 3.74 | 3.64 | 3.47 | 3.27 |
| Conservative | AGR | 89.23 | 86.16 | 83.37 | 80.82 | 75.50 | 68.13 |
| | Retention % | 100 | 87.24 | 76.41 | 67.09 | 53.77 | 40.57 |

Panel C: AGR deciles

| Decile | Statistic | M | M+1 | M+2 | M+3 | M+6 | M+12 |
|---|---|---|---|---|---|---|---|
| | Decile | 1.00 | 1.28 | 1.54 | 1.76 | 2.28 | 3.11 |
| D1 | AGR | 6.61 | 9.12 | 11.42 | 13.53 | 18.44 | 26.37 |
| | Retention % | 100 | 86.48 | 74.84 | 64.84 | 50.18 | 34.66 |
| | Decile | 2.00 | 2.30 | 2.58 | 2.82 | 3.32 | 3.99 |
| D2 | AGR | 17.08 | 19.78 | 22.27 | 24.51 | 28.93 | 35.05 |
| | Retention % | 100 | 77.16 | 58.28 | 42.68 | 28.54 | 20.08 |
| | Decile | 3.00 | 3.24 | 3.46 | 3.66 | 4.02 | 4.50 |
| D3 | AGR | 26.65 | 28.72 | 30.62 | 32.38 | 35.61 | 39.90 |
| | Retention % | 100 | 74.87 | 54.52 | 37.54 | 23.58 | 17.13 |
| | Decile | 4.00 | 4.15 | 4.28 | 4.41 | 4.65 | 4.92 |
| D4 | AGR | 35.81 | 37.10 | 38.30 | 39.41 | 41.53 | 43.87 |
| | Retention % | 100 | 73.89 | 52.48 | 34.92 | 21.28 | 15.76 |
| | Decile | 5.00 | 5.07 | 5.12 | 5.17 | 5.25 | 5.33 |
| D5 | AGR | 44.91 | 45.46 | 45.94 | 46.40 | 47.10 | 47.68 |
| | Retention % | 100 | 73.20 | 51.52 | 34.57 | 20.81 | 15.13 |
| | Decile | 6.00 | 5.96 | 5.93 | 5.91 | 5.83 | 5.73 |
| D6 | AGR | 54.06 | 53.77 | 53.53 | 53.25 | 52.53 | 51.42 |
| | Retention % | 100 | 72.85 | 51.02 | 33.84 | 19.85 | 14.56 |
| | Decile | 7.00 | 6.86 | 6.74 | 6.63 | 6.42 | 6.10 |
| D7 | AGR | 63.18 | 61.98 | 60.93 | 59.95 | 58.07 | 54.95 |
| | Retention % | 100 | 74.07 | 53.05 | 35.69 | 21.15 | 14.66 |
| | Decile | 8.00 | 7.77 | 7.55 | 7.36 | 6.99 | 6.48 |
| D8 | AGR | 72.50 | 70.45 | 68.54 | 66.78 | 63.43 | 58.53 |
| | Retention % | 100 | 74.97 | 54.51 | 37.80 | 23.77 | 16.42 |
| | Decile | 9.00 | 8.70 | 8.42 | 8.17 | 7.66 | 6.99 |
| D9 | AGR | 82.39 | 79.62 | 77.06 | 74.71 | 69.91 | 63.48 |
| | Retention % | 100 | 76.99 | 58.38 | 42.81 | 28.39 | 20.32 |
| | Decile | 10.00 | 9.66 | 9.35 | 9.07 | 8.51 | 7.72 |
| D10 | AGR | 93.07 | 89.91 | 87.02 | 84.38 | 78.81 | 70.88 |
| | Retention % | 100 | 85.00 | 72.58 | 61.54 | 46.78 | 32.77 |

## Table 4.4: AGR score and operating performance: ROA

We tabulate OLS estimates of the pooled annual regression of return on assets (ROA) on the AGR score and additional cross-sectional controls. Panel A uses AGR scores and Panel B uses AGR groups. AGR($t$) is the last rating available in year $t$. In specifications (1) to (4), the dependent variable is the contemporaneous ROA, ROA($t$). In specifications (5) to (8), the dependent variable is the ROA in fiscal year $t+2$, ROA($t+2$). ROA is computed as ratio of Operating Income After Depreciation in the current fiscal year to Assets at the end of the prior fiscal year. For a given firm-year, ROA is then adjusted by subtracting the median ROA in the industry, as defined by its three-digit SIC code. Delaware is a dummy that equals one for firms incorporated in Delaware. $t$-statistics based on heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. All regressions include a constant term, whose coefficient is omitted. Sample period is January 1997 to December 2011.

| Dep. Var. | ROA($t$) | | | | ROA($t+2$) | | | |
|---|---|---|---|---|---|---|---|---|
| **Panel A: AGR score** | | | | | | | | |
| Variable ($t$) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| AGR score | -0.002 | 0.056*** | -0.003 | 0.012* | 0.011*** | 0.030*** | 0.010*** | 0.015** |
| | (0.004) | (0.008) | (0.003) | (0.006) | (0.003) | (0.005) | (0.003) | (0.006) |
| Log(Market Value) | | 3.729*** | | 1.743** | | -0.880 | | -2.264*** |
| | | (0.818) | | (0.789) | | (0.562) | | (0.680) |
| Log(Assets) | | 1.633* | | 3.641*** | | 2.530*** | | 2.275** |
| | | (0.856) | | (1.184) | | (0.576) | | (1.084) |
| CAPEX/Assets | | 7.224 | | 1.926 | | 6.685* | | 3.425 |
| | | (6.175) | | (4.750) | | (3.753) | | (4.846) |
| Leverage | | -10.469*** | | -6.165** | | 0.910 | | 0.139 |
| | | (1.982) | | (2.403) | | (1.471) | | (2.330) |
| R&D/Sales | | -0.004* | | -0.001 | | -0.003*** | | -0.001** |
| | | (0.002) | | (0.001) | | (0.001) | | (0.000) |
| Log(Tobin's Q) | | -3.344** | | 4.081*** | | 1.672** | | 5.466*** |
| | | (1.314) | | (1.268) | | (0.831) | | (1.046) |
| Delaware | | -4.319*** | | | | -1.188*** | | |
| | | (0.685) | | | | (0.359) | | |
| ROA, Ind. Adj. | | | | | 0.624*** | 0.593*** | | |
| | | | | | (0.012) | (0.015) | | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Fixed Effects | No | No | Yes | Yes | No | No | Yes | Yes |
| Obs. | 47,896 | 22,094 | 47,896 | 22,094 | 36,116 | 16,640 | 36,116 | 16,640 |
| $R^2$ | 0.002 | 0.191 | 0.695 | 0.725 | 0.004 | 0.520 | 0.729 | 0.752 |
| **Panel B: AGR groups** | | | | | | | | |
| Variable (t) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Aggressive | 1.398*** | 3.016*** | 0.522* | 1.201** | 0.399 | 0.241 | 0.580** | 0.461 |
| | (0.413) | (0.661) | (0.303) | (0.536) | (0.287) | (0.509) | (0.288) | (0.519) |
| Average | 1.592*** | 5.198*** | 0.516* | 1.765*** | 0.772*** | 1.247** | 0.769*** | 0.729 |
| | (0.423) | (0.685) | (0.309) | (0.556) | (0.275) | (0.493) | (0.296) | (0.536) |
| Conservative | 0.519 | 5.593*** | 0.074 | 1.379** | 0.987*** | 2.376*** | 1.027*** | 1.276** |
| | (0.467) | (0.805) | (0.350) | (0.654) | (0.312) | (0.563) | (0.345) | (0.622) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Fixed Effects | No | No | Yes | Yes | No | No | Yes | Yes |
| Obs. | 48,139 | 22,214 | 48,139 | 22,214 | 36,551 | 16,942 | 36,661 | 16,996 |
| $R^2$ | 0.043 | 0.185 | 0.665 | 0.698 | 0.465 | 0.494 | 0.706 | 0.728 |

## Table 4.5: AGR score and operating performance: other measures

We tabulate OLS estimates of pooled annual regressions of operating performance measures on the AGR score and additional cross-sectional controls. The measures are Tobin's Q, Net Margin, and 3-Year Sales Growth. The dependent variable is industry-adjusted by subtracting its median value in the industry, as defined by three-digit SIC code. Delaware is a dummy that equals one for firms incorporated in Delaware. $t$-statistics based on heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. All regressions include a constant term, whose coefficient is omitted. Sample period is January 1997 to December 2011.

| Dep. Var. | Tobin's Q($t+2$) | | Net Margin($t+2$) | | 3-Year Sales growth($t+2$) | |
|---|---|---|---|---|---|---|
| | | | Panel A: AGR score | | | |
| Control (t) | (1) | (2) | (3) | (4) | (5) | (6) |
| AGR score | 0.117*** | 0.061 | 0.049*** | 0.081*** | 0.056** | -0.049 |
| | (0.029) | (0.046) | (0.015) | (0.030) | (0.025) | (0.040) |
| Log(Market Value) | | 10.998*** | | -5.284 | | 8.379 |
| | | (2.483) | | (4.211) | | (6.840) |
| Log(Assets) | | -67.312*** | | -0.073 | | -60.082*** |
| | | (4.490) | | (5.808) | | (8.558) |
| CAPEX/Assets | | -47.523 | | 52.545** | | 6.338 |
| | | (34.920) | | (26.180) | | (35.826) |
| Leverage | | 30.420*** | | 36.168** | | 4.809 |
| | | (10.633) | | (17.516) | | (17.572) |
| R&D/Sales | | 0.001 | | -0.011 | | -0.009 |
| | | (0.010) | | (0.012) | | (0.007) |
| Log(Tobin's Q) | | | | 4.878 | | -18.179* |
| | | | | (6.014) | | (9.846) |
| ROA | | | | | | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 32,465 | 16,897 | 36,456 | 16,930 | 27,390 | 12,671 |
| $R^2$ | 0.631 | 0.640 | 0.722 | 0.734 | 0.453 | 0.498 |
| | | | Panel B: AGR groups | | | |
| Control (t) | (1) | (2) | (3) | (4) | (5) | (6) |
| Aggressive | 2.010 | -1.954 | 2.630* | 3.321 | 4.275* | 2.526 |
| | (2.360) | (3.786) | (1.470) | (2.812) | (2.314) | (3.860) |
| Average | 8.078*** | 3.764 | 3.581** | 4.731 | 6.593*** | 2.131 |
| | (2.429) | (3.829) | (1.524) | (2.927) | (2.326) | (3.771) |
| Conservative | 9.277*** | 1.460 | 5.547*** | 8.251** | 4.522* | -4.245 |
| | (2.883) | (4.575) | (1.697) | (3.369) | (2.550) | (4.152) |
| Controls | No | Yes | No | Yes | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 32,465 | 16,897 | 36,456 | 16,930 | 27,390 | 12,671 |
| $R^2$ | 0.631 | 0.640 | 0.722 | 0.734 | 0.453 | 0.498 |

### Table 4.6: AGR score and operating performance: additional analyses

We tabulate the results of the OLS pooled annual regression of future industry-adjusted operating performance measures. In Panel A, the independent variable is the year-$t$ AGR decile. In Panel B, the independent variable is the year-$t$ AGR rating when companies in the lowest AGR decile (D1) in that year are removed from the sample. In Panel C, the independent variable is the year-$t$ AGR rating interacted with dummies for the three subsamples 1997-2001, 2002-2006, and 2007-2012. $t$-statistics based on heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. All regressions include a constant term, whose coefficient is omitted. The sample period is January 1997 to December 2011.

Panel A: AGR deciles

| | ROA$(t+2)$ | Tobin's Q$(t+2)$ | Net Margin$(t+2)$ | 3-Year Sales growth$(t+2)$ |
|---|---|---|---|---|
| AGR decile (t) | 0.089*** | 1.051*** | 0.465*** | 0.550** |
| | (0.030) | (0.262) | (0.142) | (0.231) |
| Obs. | 36,661 | 32,465 | 36,456 | 27,390 |
| $R^2$ | 0.706 | 0.631 | 0.722 | 0.453 |

Panel B: Dropping firms in AGR decile D1

| | ROA$(t+2)$ | Tobin's Q$(t+2)$ | Net Margin$(t+2)$ | 3-Year Sales growth$(t+2)$ |
|---|---|---|---|---|
| AGR (t) | 0.006* | 0.109*** | 0.031** | 0.044 |
| | (0.003) | (0.031) | (0.015) | (0.000) |
| Obs. | 32,768 | 29,055 | 32,600 | 24,446 |
| $R^2$ | 0.711 | 0.640 | 0.733 | 0.487 |

Panel C: Subsamples

| | ROA$(t+2)$ | Tobin's Q$(t+2)$ | Net Margin$(t+2)$ | 3-Year Sales growth$(t+2)$ |
|---|---|---|---|---|
| AGR (t) $\times \mathbb{1}_{1997-2003}$ | 0.009* | 0.079* | 0.062*** | -0.011 |
| | (0.005) | (0.042) | (0.023) | (0.031) |
| AGR (t) $\times \mathbb{1}_{2004-2011}$ | 0.011*** | 0.153*** | 0.036* | 0.160*** |
| | (0.004) | (0.034) | (0.020) | (0.034) |
| Obs. | 36,661 | 32,465 | 36,456 | 27,390 |
| $R^2$ | 0.700 | 0.620 | 0.716 | 0.443 |

## Table 4.7: Performance analysis of AGR sorted portfolios

At the beginning of each month, stocks are grouped into Very Aggressive, Aggressive, Average, and Conservative groups based on their AGR score reported at the end of the prior month. We compute value-weighted (VW) and equal-weighted (EW) returns to these portfolios as well as the portfolio which goes long shares of Conservative firms and short share of Very Aggressive firms. The groups are then rebalanced every month. We report estimates of the following regression:

$$r_{p,t} = \alpha + \beta_1 \mathrm{RMRF}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{UMD}_t + \beta_5 \mathrm{RMW} + \beta_6 \mathrm{CMA} + \beta_7 \mathrm{ACC}_t + \beta_8 \mathrm{SUE}_t + \epsilon_{p,t}$$

The risk factors are the following zero-investment portfolios: the three Fama and French (1993) factors capturing exposure to the market (RMRF), size (SMB), and book-to-market (HML); the momentum factor UMD of Fama and French (1996); RWA is the difference between the returns on diversified portfolios of stocks with robust and weak profitability; CMA is the difference between the returns on diversified portfolios of the stocks of low and high investment firms; CMA is the accrual factor of Hirshleifer et al. (2012); SUE is a portfolio based on standardized earning surprises. $t$-statistics based on Newey and West (1987) standard errors with 3 lags are reported in parentheses. *Alpha* is the intercept estimate and measures the monthly abnormal return, in percentage terms. Panel A uses returns in excess of the 3-month T-bill rate, while Panel B uses industry-adjusted returns. The sample period is January 2005 to December 2011.

Panel A: Excess returns

| | VW | | | | | EW | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | VeryAgg | Agg | Avg | Cons | Cons - VeryAgg | VeryAgg | Agg | Avg | Cons | Cons - VeryAgg |
| *Alpha* | -0.451 | 0.004 | 0.155 | 0.090 | 0.541 | -0.337 | 0.013 | 0.141 | 0.179 | 0.516 |
| | (-2.74) | (0.05) | (2.60) | (1.26) | (3.03) | (-2.07) | (0.16) | (2.23) | (2.51) | (3.25) |
| RMRF | 1.043 | 1.005 | 0.960 | 0.940 | -0.102 | 1.022 | 0.976 | 0.952 | 0.911 | -0.111 |
| | (22.26) | (44.91) | (50.04) | (38.51) | (-1.55) | (24.25) | (30.53) | (55.02) | (48.25) | (-2.10) |
| SMB | 0.508 | 0.627 | 0.667 | 0.624 | 0.117 | 0.626 | 0.766 | 0.750 | 0.657 | 0.031 |
| | (6.87) | (18.86) | (21.63) | (14.67) | (1.29) | (8.60) | (16.56) | (22.26) | (14.11) | (0.34) |
| HML | 0.230 | 0.130 | 0.146 | 0.173 | -0.057 | 0.171 | 0.145 | 0.154 | 0.145 | -0.026 |
| | (3.56) | (4.34) | (3.69) | (3.76) | (-0.69) | (2.79) | (3.59) | (4.35) | (2.69) | (-0.37) |
| UMD | -0.195 | -0.112 | -0.083 | 0.025 | 0.219 | -0.203 | -0.158 | -0.107 | -0.027 | 0.176 |
| | (-4.62) | (-3.95) | (-4.15) | (1.07) | (5.63) | (-4.60) | (-5.50) | (-5.14) | (-0.93) | (4.39) |
| RMW | -0.333 | -0.055 | -0.104 | -0.052 | 0.281 | -0.411 | -0.174 | -0.131 | -0.116 | 0.294 |
| | (-3.00) | (-0.97) | (-2.04) | (-0.84) | (2.24) | (-3.76) | (-2.53) | (-2.50) | (-1.75) | (2.37) |
| CMA | -0.066 | -0.121 | -0.128 | -0.062 | 0.004 | -0.090 | -0.162 | -0.154 | -0.036 | 0.054 |
| | (-0.51) | (-2.15) | (-2.24) | (-1.04) | (0.03) | (-0.81) | (-2.41) | (-2.77) | (-0.48) | (0.54) |
| ACC | -0.064 | -0.045 | 0.015 | 0.037 | 0.101 | 0.088 | 0.047 | 0.073 | 0.016 | -0.072 |
| | (-0.50) | (-0.63) | (0.30) | (0.77) | (0.74) | (0.64) | (0.56) | (1.52) | (0.31) | (-0.47) |
| SUE | 0.060 | -0.024 | -0.020 | -0.065 | -0.125 | 0.057 | -0.023 | -0.028 | -0.040 | -0.098 |
| | (1.09) | (-0.92) | (-0.67) | (-1.71) | (-1.89) | (0.93) | (-0.92) | (-1.09) | (-0.95) | (-1.22) |
| $R^2$ | 0.963 | 0.988 | 0.991 | 0.987 | 0.49 | 0.964 | 0.986 | 0.991 | 0.987 | 0.515 |

Panel B: Industry-adjusted returns

| | VW | | | | | EW | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | VeryAgg | Agg | Avg | Cons | Cons - VeryAgg | VeryAgg | Agg | Avg | Cons | Cons - VeryAgg |
| *Alpha* | -0.431 | -0.043 | 0.126 | 0.132 | 0.562 | -0.403 | -0.023 | 0.144 | 0.177 | 0.580 |
| | (-2.46) | (-0.62) | (2.19) | (1.87) | (3.27) | (-2.32) | (-0.32) | (2.23) | (2.68) | (3.73) |
| RMRF | 0.017 | -0.045 | -0.074 | -0.066 | -0.083 | -0.017 | -0.077 | -0.093 | -0.096 | -0.079 |
| | (0.34) | (-2.50) | (-3.31) | (-3.54) | (-1.38) | (-0.38) | (-2.91) | (-4.11) | (-4.68) | (-1.61) |
| SMB | 0.371 | 0.458 | 0.449 | 0.415 | 0.044 | 0.438 | 0.529 | 0.492 | 0.430 | -0.009 |
| | (4.30) | (20.49) | (18.44) | (13.53) | (0.50) | (4.97) | (16.47) | (16.89) | (11.14) | (-0.09) |
| HML | 0.193 | 0.147 | 0.148 | 0.127 | -0.066 | 0.170 | 0.131 | 0.139 | 0.100 | -0.070 |
| | (2.70) | (6.29) | (4.04) | (3.45) | (-0.81) | (2.53) | (4.27) | (4.28) | (2.39) | (-0.99) |
| UMD | -0.124 | -0.032 | -0.024 | 0.046 | 0.170 | -0.127 | -0.053 | -0.035 | 0.011 | 0.138 |
| | (-3.23) | (-1.81) | (-1.54) | (2.61) | (4.63) | (-3.33) | (-2.81) | (-2.40) | (0.47) | (3.62) |
| RMW | -0.296 | -0.043 | -0.045 | -0.030 | 0.266 | -0.343 | -0.129 | -0.092 | -0.064 | 0.279 |
| | (-2.66) | (-0.94) | (-1.01) | (-0.57) | (2.31) | (-3.20) | (-2.63) | (-1.99) | (-1.24) | (2.42) |
| CMA | -0.017 | -0.043 | -0.018 | 0.028 | 0.045 | -0.039 | -0.058 | -0.043 | 0.052 | 0.091 |
| | (-0.13) | (-0.81) | (-0.32) | (0.60) | (0.40) | (-0.33) | (-1.01) | (-0.75) | (0.77) | (0.98) |
| ACC | 0.091 | -0.064 | -0.013 | 0.049 | -0.042 | 0.168 | 0.035 | 0.080 | 0.042 | -0.126 |
| | (0.67) | (-1.04) | (-0.24) | (1.05) | (-0.32) | (1.15) | (0.45) | (1.38) | (0.73) | (-0.92) |
| SUE | 0.100 | -0.008 | -0.016 | -0.007 | -0.107 | 0.098 | -0.008 | -0.011 | 0.033 | -0.064 |
| | (1.77) | (-0.39) | (-0.56) | (-0.22) | (-1.67) | (1.70) | (-0.39) | (-0.48) | (0.96) | (-0.87) |
| $R^2$ | 0.588 | 0.798 | 0.817 | 0.761 | 0.444 | 0.607 | 0.799 | 0.827 | 0.708 | 0.476 |

### Table 4.8: Fama-MacBeth regressions

We provide the results of the OLS cross-sectional regression of stock returns:

$$r_{i,t+1} = \gamma_{0,t} + \gamma'_{1,t}\mathbf{X}_{i,t} + \epsilon_{i,t+1}$$

on various combinations of the regressors in $\mathbf{X}$. AGR is the AGR score at the end of month $t$. $MV$ and *Book-to-Market* denote, respectively, the log of stock market capitalization and book-to-market ratio at the end of the prior fiscal year. *Ret(t)* is the return in month $t$, while *Ret(t-12:t-1)* denotes the cumulative return in months $t-12$ through $t-1$. $\beta$ is the slope coefficient in the regression of excess stock returns on a constant and RMRF estimated on the 60-month period ending in month $t$. Idiosyncratic volatility $iv$ is measured by the square root of average squared residuals from a 3-factor Fama and French (1993) model estimated using daily returns in month $t$ as in Ang et al. (2006). *Accrual* is the most recent accrual. *SUE* is the most recent earnings surprise. The regressions are estimated separately each month from January 2005 to December 2011. We tabulate average coefficients with the corresponding $t$-statistic based on Newey and West (1987) standard errors with 3 lags in parentheses. Returns are expressed in percentage.

| Control | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| AGR | 0.006 | 0.005 | 0.005 | | 0.005 |
| | (2.93) | (4.11) | (2.79) | | (3.86) |
| $\beta$ | | 0.179 | | 0.163 | 0.180 |
| | | (0.75) | | (0.69) | (0.76) |
| log(MV) | | -0.083 | | -0.100 | -0.088 |
| | | (-1.43) | | (-1.76) | (-1.52) |
| log(Book-to-Market) | | -0.002 | | 0.013 | 0.006 |
| | | (-0.03) | | (0.22) | (0.11) |
| *Ret(t)* | | -2.871 | | -2.896 | -2.905 |
| | | (-4.02) | | (-4.06) | (-4.07) |
| *Ret(t-12:t-1)* | | 0.032 | | 0.028 | 0.018 |
| | | (0.12) | | (0.11) | (0.07) |
| $iv$ | | -5.373 | | -6.224 | -5.736 |
| | | (-0.91) | | (-1.05) | (-0.98) |
| Accrual | | | -1.952 | -1.851 | -1.763 |
| | | | (-3.64) | (-3.98) | (-3.79) |
| SUE | | | 0.019 | 0.025 | 0.023 |
| | | | (1.15) | (2.26) | (2.09) |

## Table 4.9: CDS spread and AGR rating: Future

This table reports the regression coefficients of regressing monthly CDS spreads on the lag AGR scores and a set of controls. The dependent variables are the CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA), stock volatility and market return. See Appendix A for a detailed description of the variables. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | CDS | CDS | ln(CDS) | ln(CDS) |
|---|---|---|---|---|
| lag_AGR score | -0.305** | -0.238** | -0.00130*** | -0.000809** |
| | (-2.01) | (-1.98) | (-3.40) | (-2.49) |
| Size | | -20.78 | | 0.0457 |
| | | (-1.60) | | (0.94) |
| Leverage | | 224.8*** | | 1.184*** |
| | | (3.84) | | (7.30) |
| CDS depth | | 10.63** | | 0.0526*** |
| | | (2.14) | | (3.12) |
| ROA | | -371.0*** | | -1.719*** |
| | | (-5.96) | | (-6.49) |
| Stock Return | | -26.14 | | -0.0385 |
| | | (-1.07) | | (-1.50) |
| Stock Volatility | | 1789.6*** | | 2.903*** |
| | | (10.00) | | (11.74) |
| Market Return | | -4656.1*** | | -20.89*** |
| | | (-5.46) | | (-22.19) |
| N | 50900 | 48612 | 50900 | 48612 |
| R-squared | 0.563 | 0.633 | 0.797 | 0.835 |
| Rating FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm |

### Table 4.10: CDS Spreads and AGR Rating: Contemporaneous

This table reports the regression coefficients of regressing monthly CDS spreads on the contemporaneous AGR scores and a set of controls. The dependent variables are the CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA), stock volatility and market return. See Appendix A for a detailed description of the variables. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | CDS | CDS | ln(CDS) | ln(CDS) |
|---|---|---|---|---|
| AGR score | -0.315** | -0.255** | -0.00131*** | -0.000839*** |
| | (-2.05) | (-2.12) | (-3.39) | (-2.58) |
| Size | | -21.05 | | 0.0450 |
| | | (-1.62) | | (0.93) |
| Leverage | | 224.6*** | | 1.183*** |
| | | (3.83) | | (7.30) |
| CDS depth | | 10.68** | | 0.0528*** |
| | | (2.15) | | (3.13) |
| ROA | | -371.2*** | | -1.720*** |
| | | (-5.97) | | (-6.49) |
| Stock Return | | -26.17 | | -0.0386 |
| | | (-1.08) | | (-1.50) |
| Stock Volatility | | 1789.4*** | | 2.903*** |
| | | (10.00) | | (11.74) |
| Market Return | | -4670.8*** | | -20.94*** |
| | | (-5.47) | | (-22.25) |
| N | 50900 | 48612 | 50900 | 48612 |
| R-squared | 0.563 | 0.633 | 0.797 | 0.835 |
| Rating FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm |

### Table 4.11: CDS Spreads and G-Index

This table reports the regression coefficients of regressing monthly CDS spreads on the G_index—Gompers et al. (2003) and a set of controls. The dependent variables are the CDS spreads while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA), stock volatility and market return. Regressions also contain rating, firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | CDS | CDS | CDS | CDS | CDS |
|---|---|---|---|---|---|
| G_Index | -4.282* | -0.373 | -14.04 | -15.03 | -15.05 |
| | (-1.77) | (-0.27) | (-0.98) | (-1.06) | (-1.11) |
| Size | | 4.796 | | | 71.60** |
| | | (0.65) | | | (2.20) |
| Leverage | | 242.0*** | | | 247.9 |
| | | (5.31) | | | (1.44) |
| CDS depth | | -35.01*** | | | -20.72 |
| | | (-4.04) | | | (-1.55) |
| ROA | | -368.1*** | | | -308.6 |
| | | (-4.84) | | | (-1.53) |
| Stock Return | | 99.02 | | | 148.9 |
| | | (0.72) | | | (0.74) |
| Stock Volatility | | 1875.0*** | | | 2219.3*** |
| | | (5.04) | | | (4.05) |
| Market Return | | -12180.6** | | | -31285.5 |
| | | (-2.17) | | | (-1.28) |
| constant | 155.1*** | -59.61 | | | |
| | (5.57) | (-0.70) | | | |
| N | 1117 | 1030 | 1042 | 1042 | 945 |
| R-squared | 0.00219 | 0.441 | 0.549 | 0.555 | 0.669 |
| Rating FE | | | Yes | Yes | Yes |
| Firm FE | | | Yes | Yes | Yes |
| Time FE | | | Yes | Yes | Yes |
| Cluster | | | Firm | Firm | Firm |

### Table 4.12: Credit Ratings and AGR rating

Logistic regression results of the effects of corporate governance attributes on firms' credit ratings. The dependent variables are monthly credit ratings while the relevant independent variables are firm size, liquidity, leverage, profitability (ROA), stock volatility, market return, interest coverage, and operating loss. See Appendix A for a detailed description of the variables. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | Credit score | Credit score | Credit score |
|---|---|---|---|
| lag_AGR score | 0.00605*** | | |
| | (5.48) | | |
| AGR | | 0.00595*** | |
| | | (5.39) | |
| G_Index | | | 0.122*** |
| | | | (4.41) |
| Size | 0.815*** | 0.814*** | 0.949*** |
| | (16.30) | (16.29) | (12.95) |
| Leverage | -3.363*** | -3.363*** | -3.663*** |
| | (-13.16) | (-13.17) | (-7.30) |
| ROA | 5.939*** | 5.945*** | 7.635*** |
| | (9.28) | (9.29) | (7.88) |
| Stock Return | -0.384*** | -0.384*** | -0.487 |
| | (-7.79) | (-7.78) | (-0.71) |
| Stock Volatility | -9.597*** | -9.593*** | -19.32*** |
| | (-17.24) | (-17.23) | (-10.09) |
| Market Return | -7.309*** | -7.326*** | -410.5*** |
| | (-3.01) | (-3.02) | (-15.42) |
| Interest coverage | -0.000222*** | -0.000222*** | -0.0000977*** |
| | (-7.64) | (-7.64) | (-6.55) |
| Operating loss | -0.185** | -0.185** | -0.231 |
| | (-2.27) | (-2.28) | (-1.40) |
| N | 106565 | 106565 | 1552 |
| Cluster | Firm | Firm | Firm |

### Table 4.13: Firm-level Yield Spreads and AGR rating

This table reports the regression coefficients of regressing monthly corporate bond spreads on the governance variables and a set of controls. The dependent variables are the yield spreads while the relevant independent variables are duration, bond age, rating score, firm size, leverage, profitability (ROA), and stock volatility. See Appendix A for a detailed description of the variables. Regressions also contain firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | Yield | Yield | Yield | Yield | Yield | Yield |
|---|---|---|---|---|---|---|
| lag_AGR score | -0.00225* | -0.00257* | | | | |
| | (-1.71) | (-1.93) | | | | |
| AGR | | | -0.00253* | -0.00268** | | |
| | | | (-1.90) | (-2.02) | | |
| G_Index | | | | | -0.189** | -0.156* |
| | | | | | (-2.49) | (-1.80) |
| Duration | | -0.163*** | | -0.163*** | | -0.00424 |
| | | (-5.66) | | (-5.65) | | (-0.14) |
| Bond_age | | 0.0434*** | | 0.0434*** | | 0.0326 |
| | | (3.10) | | (3.11) | | (0.96) |
| Rating_score | | 0.298*** | | 0.298*** | | 0.237*** |
| | | (9.17) | | (9.17) | | (4.03) |
| Size | | 0.0574 | | 0.0557 | | 0.825*** |
| | | (0.46) | | (0.44) | | (3.19) |
| Leverage | | 1.681** | | 1.681** | | 1.076 |
| | | (2.47) | | (2.47) | | (1.11) |
| ROA | | -4.015*** | | -4.018*** | | -5.267*** |
| | | (-3.90) | | (-3.90) | | (-3.18) |
| Stock Volatility | | 14.61*** | | 14.60*** | | 8.080*** |
| | | (11.71) | | (11.71) | | (4.14) |
| N | 60520 | 42487 | 60520 | 42487 | 1484 | 976 |
| R-squared | 0.509 | 0.583 | 0.509 | 0.583 | 0.735 | 0.792 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm | Firm | Firm |

### Table 4.14: Security-level Yield Spreads and AGR rating

This table reports the regression coefficients of regressing monthly corporate bond spreads on the governance variables and a set of controls. The dependent variables are the security-level yield spreads while the relevant independent variables are issue characteristics (such as issue size, number of years to maturity, dummies for callability, senior and senior-secured debt, duration, and credit ratings) and issuer characteristics (leverage, ROA, size, stock volatility). See Appendix A for a detailed description of the variables. Regressions also contain firm and time fixed effects. Standard errors are clustered by firm. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

| | Yield | Yield | Yield | Yield | Yield | Yield |
|---|---|---|---|---|---|---|
| lag_AGR score | -0.00442*** | -0.00289** | | | | |
| | (-2.62) | (-2.10) | | | | |
| AGR | | | -0.00472*** | -0.00322** | | |
| | | | (-2.80) | (-2.38) | | |
| G_Index | | | | | -0.239*** | -0.109 |
| | | | | | (-3.27) | (-1.13) |
| lsize | | -0.236*** | | -0.236*** | | -0.234** |
| | | (-4.44) | | (-4.45) | | (-2.39) |
| matur | | 0.0325*** | | 0.0325*** | | 0.0172*** |
| | | (4.32) | | (4.32) | | (5.01) |
| call | | -0.343* | | -0.342* | | -0.247 |
| | | (-1.95) | | (-1.95) | | (-1.11) |
| senior | | -0.114 | | -0.114 | | -0.0608 |
| | | (-1.18) | | (-1.18) | | (-0.54) |
| sink | | 0.301 | | 0.302 | | 0.472 |
| | | (0.70) | | (0.70) | | (1.30) |
| duration | | -0.0633*** | | -0.0633*** | | -0.0237** |
| | | (-2.70) | | (-2.70) | | (-2.01) |
| rating_score | | 0.347*** | | 0.347*** | | 0.241*** |
| | | (7.55) | | (7.55) | | (5.52) |
| Size | | -0.230* | | -0.234* | | 0.686** |
| | | (-1.66) | | (-1.69) | | (2.34) |
| Leverage | | 1.513** | | 1.509** | | -0.673 |
| | | (2.13) | | (2.12) | | (-0.56) |
| ROA | | -4.797*** | | -4.794*** | | -6.739*** |
| | | (-5.29) | | (-5.29) | | (-3.48) |
| Stock Volatility | | 13.88*** | | 13.88*** | | 15.25*** |
| | | (7.43) | | (7.44) | | (4.36) |
| N | 229257 | 138939 | 229257 | 138939 | 7676 | 4725 |
| R-squared | 0.452 | 0.529 | 0.452 | 0.529 | 0.642 | 0.725 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Firm | Firm | Firm | Firm | Firm | Firm |

## Appendix 4.A: Definition of Variables

| Variable Name | Description | Data Source |
|---|---|---|
| CDS Spreads | 5-year maturity CDS spread for firm i in the last day of month t in basis points. ln(CDS) is the natural logarithm of 5-year CDS spread | Markit Group |
| ln(CDS) | The natural logarithm of 5-year CDS spread | Markit Group |
| Size | The natural logarithm of total book value of assets. | Compustat |
| Leverage | Total debt (the sum of long-term and short-term debt) divided by total assets. | Compustat |
| ROA | Return on assets or profitability, which is the operating income before depreciation, amortization and taxes (OIBD) divided by total assets. | Compustat |
| CDS depth | Number of distinct quote providers for each daily composite quote. Composite CDS spreads in Markit database are based on the quotes provided by market makers with the requirement of at least two contributors. | Markit Group |
| Stock Volatility | Stock return volatility, which is the standard deviation of daily stock log returns within the quarter month. | CRSP |
| Stock Return | Monthly stock return | CRSP |
| Market Return | Monthly value-weighted index. | CRSP |
| Credit Rating | Firm credit ratings are the long-term issuer credit ratings compiled by Standard&Poor's. The ratings range from AAA (highest rating) to D (lowest rating—debt in payment default). For purposes of our analysis, the multiple ratings are collapsed into seven categories following Ashbaugh-Skaife et al. (2006). | S&P Capital IQ |
| Yield (%) | Equally-weighted average yield spread of firm's senior unsecured bonds, calculated using the daily bond trade observations obtained from TRACE and the interpolated maturity-matched treasury yields. | TRACE and FISD |
| Interest coverage | Operating income before depreciation divided by interest expense. | Compustat |
| Operating Loss | 1 if the net income before extraordinary items is negative in the current and prior fiscal year, 0 otherwise. | Compustat |
| Rating score | Firm's long term credit rating prior to the event. Ratings are provided by S&P, Moody's, or Fitch, in availability order, where letter grades are converted to numerical scales from AAA (1) to D (22). | S&P Capital IQ and FISD |
| Duration | The weighted average debt duration | TRACE and FISD |
| Bond Age | The weighted age of bonds for each firm for each year as a measure of debt liquidity. | TRACE and FISD |
| lsize | Log of the size of issue (in millions of dollars). | TRACE and FISD |
| Matur | Time to maturity. | TRACE and FISD |
| Call | The ratio of the days to first call divided by the days to maturity. This variable takes the value of 1 if there is no call and 0 if it is callable from the date of issue. | TRACE and FISD |
| Senior | 1 if the debt is senior, 0 otherwise. | TRACE and FISD |
| Senior Secured | 1 if the debt is senior secured, 0 otherwise. | TRACE and FISD |
| Sink | 1 if the debt has sinking fund provisions, 0 otherwise. | TRACE and FISD |

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