Title Page

Three Essays in Corporate Finance

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Abstract

Three Essays in Corporate Finance

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This dissertation consists of three essays on corporate finance. In the first essay, I use two important rulings of Marblegate Asset Management v. Education Management Corporation (EMC) to study the effect of distressed public debt restructuring methods on investment. The 2014 ruling limited the ability of firms to use coercive bond exchange offers to facilitate out-of-court restructurings, thereby increasing the likelihood that public debt would be restructured under Chapter 11. The 2017 ruling reversed the 2014 ruling. Following the 2014 ruling, affected distressed firms significantly reduced investment and improved investment efficiency relative to non-distressed firms. Affected firms responded in an opposite manner to the 2017 ruling. I conclude that the method of public debt restructuring in distressed firms affects ex ante investment policies. In the second essay, I utilize a legal ruling that represents an exogenous shock to bankruptcy-related control threats from secured creditors to study the effect of takeover threats from secured creditors on ex ante debt financing policies. Following a positive shock to such threats, firms with high default probabilities (particularly those with high secured debt ratios) significantly decrease leverage. This effect is larger for firms that have a lower probability of being acquired in a hostile takeover and those with higher pay-performance sensitivity of CEO compensation. I conclude that bankruptcy-related takeover threats from creditors have a meaningful impact on capital structure choice, and that this impact is opposite that of equity-based takeover threats. In the third essay, I study the financing effect of prepaid gift cards. Prepaid gift cards represent short-term liabilities because retailers receive up-front cash at the sale of prepaid cards and book revenue at redemption. I show that these liabilities are economically important; the average unredeemed prepaid card balance is 7.0% of total liabilities and 3.4% of total assets. Moreover, using a unique natural experiment, I show that after a positive (negative) shock to the financing (marketing) effect of prepaid cards, retailers with high interest expense ratios increased prepaid card balances by 32.4% of the average level. Retailers in competitive markets reduced prepaid card balances by 44.1% of the average level. Meanwhile, the amount (time-to-maturity) of bank loans decreased (increased) for retailers. In addition, prepaid card balances experience a sharp increase following debt covenant violations. Overall, the study implies that the financing benefit of receiving up-front cash is one of the reasons for retailers to sell prepaid cards. Retailers use prepaid cards to substitute short-term bank loans and trade credits.

Table of Contents

List of Tables

List of Figures

Preface

This dissertation would not have been possible without the help and support from kind people around me. I would like to thank my dissertation committee: David Denis, Diane Denis, Andrew Koch, Frederik Schlingemann, and Peter Oh. I am especially grateful to my advisor, David Denis, for his help, support, and patience during my doctoral study. I also benefit a lot from the help of all other faculty members, staff members, and fellow PhD students at the University of Pittsburgh. I thank Katz Graduate School of Business for the financial support. Finally, I would like to thank my family members for their love and support.

1.0 Chapter 1 Introduction

The three essays in this dissertation examine corporate financial distress resolution and financial policies.

In the first essay, I use two important rulings of Marblegate Asset Management v. Education Management Corporation (EMC) to study the effect of distressed public debt restructuring methods on investment. The 2014 ruling limited the ability of firms to use coercive bond exchange offers to facilitate out-of-court restructurings, thereby increasing the likelihood that public debt would be restructured under Chapter 11. The 2017 ruling reversed the 2014 ruling. Following the 2014 ruling, affected distressed firms significantly reduced investment and improved investment efficiency relative to non-distressed firms. Affected firms responded in an opposite manner to the 2017 ruling. I conclude that the method of public debt restructuring in distressed firms affects ex ante investment policies.

In the second essay, I utilize a legal ruling that represents an exogenous shock to bankruptcy-related control threats from secured creditors to study the effect of takeover threats from secured creditors on ex ante debt financing policies. Following a positive shock to such threats, firms with high default probabilities (particularly those with high secured debt ratios) significantly decrease leverage. This effect is larger for firms that have a lower probability of being acquired in a hostile takeover and those with higher pay-performance sensitivity of CEO compensation. I conclude that bankruptcy-related takeover threats from creditors have a meaningful impact on capital structure choice, and that this impact is opposite that of equity-based takeover threats.

In the third essay, I study the financing effect of prepaid gift cards. Prepaid gift cards represent short-term liabilities because retailers receive up-front cash at the sale of prepaid cards and book revenue at redemption. I show that these liabilities are economically important; the average unredeemed prepaid card balance is 7.0% of total liabilities and 3.4% of total assets. Moreover, using a unique natural experiment, I show that after a positive (negative) shock to the financing (marketing) effect of prepaid cards, retailers with high interest expense ratios increased prepaid card balances by 32.4% of the average level. Retailers in competitive markets reduced prepaid card balances by 44.1% of the average level. Meanwhile, the amount (time-to-maturity) of bank loans decreased (increased) for retailers. In addition, prepaid card balances experience a sharp increase following debt covenant violations. Overall, the study implies that the financing benefit of receiving up-front cash is one of the reasons for retailers to sell prepaid cards. Retailers use prepaid cards to substitute short-term bank loans and trade credits.

2.0 Chapter 2 Coercive Bond Exchange Offer and Corporate Investment

2.1 Introduction

Stockholders of financially distressed firms can choose to restructure public-traded debt either out-of-court or in-court. Prior research establishes that these two solutions to financial distress differ substantially in terms of direct costs, indirect costs, and violation of absolute priority (Gilson, John, and Lang, 1991; Gilson, 1991; Franks and Torous, 1994). Previous research studies the impact of out-of-court private renegotiation of private loans on investment policies (e.g., Denis and Wang, 2014). For reasons I will describe below, firms usually restructure public-traded debt out-of-court using a different method called coercive exchange offer. In this study, I analyze whether the two primary methods of distressed restructurings of public-traded debt (out-of-court through coercive bond exchange offers versus in-court) differ in terms of ex-ante investment incentives.

Previous theoretical research predicts that the restructuring methods of public-traded debt influence the level and efficiency of corporate investment. Because out-of-court restructuring is more effective in eliminating debt-overhang and reducing firm's debt burden, models consistently predict that out-of-court restructurings will lead to greater investment than Chapter 11 restructurings (See, e.g., Myers, 1977; Gertner and Scharfstein, 1991; Mooradian, 1994; Favara, Morellec, Schroth, and Valta, 2017). The predictions on investment efficiency are mixed. Myers (1977) and Favara, Morellec, Schroth, and Valta (2017) implicitly predict that out-of-court restructuring of public-traded debt improves investment efficiency because it prevents underinvestment. However, Gertner and Scharfstein (1991) and Bernardo and Talley (1996) show that out-of-court restructuring of public-traded debt can have a negative effect on investment efficiency because it induces distressed firms to overinvest or choose stochastically dominated projects.

Although these issues have been analyzed theoretically, there is little empirical evidence on the real effects of distressed restructuring methods of public-traded debts. Testing for a causal link between restructuring methods and investment is challenging because firms with public-traded debt do not randomly choose between out-of-court restructuring and Chapter 11. To overcome this challenge, I rely on two legal rulings as exogenous shocks to distressed firms' ability to restructure public-traded debt out-of-court to show that out-of-court restructuring of public debt increases investment and lowers investment efficiency in distressed firms.

Franks and Torous (1994) find that 78% of distressed firms file for bankruptcy only after failing to resolve their financial difficulties out-of-court. In out-of-court restructurings, most public-traded debts are restructured using coercive exchange offers because of the Trust Indenture Act of 1939 (TIA). The reason for firms to choose this indirect approach over direct negotiation widely used for loans or private credit agreements is that the TIA prohibits amendment of payment without unanimous consent outside of bankruptcy. Details of the TIA are discussed in Section 2.2. In exchange offers, tendering bondholders obtain stocks, cash, or new bonds with less advantageous terms in exchange for their bonds. Dissenting bondholders can still reject the offer and keep original bonds. However, exchange offers can easily fail because of low participating rates caused by the holdout problem. The free-riding holdout problem arises because minority bondholders will reject the offer and insist on full repayment after a successful exchange offer relieves firm's debt burden. Since the 1980s, exit consent has been widely used as a coercive technique in exchange offers to resolve this holdout problem. Exit consent requires the consent of tendering bondholders (the majority of outstanding bonds) to vote to change some of the protective covenants of original bond indentures as a condition to participating in the exchange offer, leaving non-tendering bondholders with bonds of reduced value. This coercive technique utilizes the coordination costs and risk aversion concerns among bondholders to create a prisoner's dilemma. As a result, bondholders might consent even if it is not in their collective interest (Kahan and Tuckman, 1993). If distressed firms with public-trade bonds fail to use coercive bond exchange offers to reduce bond repayment and extend maturity, then they probably have no option but to file for bankruptcy.

It still remains uncertain whether coercive bond exchange offers with exit consent are legitimate because of courts' different interpretations of the TIA. I utilize an influential ruling of *Marblegate Asset Management v. Education Management Corporation* (EMC) in the US District Court for the Southern District of New York in 2014 to create an exogenous negative shock to coercive bond exchange. Prior to *EMC*, courts and lawyers usually interpreted the TIA narrowly, allowing coercive bond exchange offers to be common as long as no 'core' term is amended[1]. It is relatively easy for firms to restructure public debt out-of-court and avoid bankruptcy. However, the EMC ruling significantly broadens previous interpretations of the TIA and argues that coercive bond exchange offer with exit consent violates the TIA. As a result, it increases the uncertainty that firms can successfully restructure public-traded debt and avoid entering bankruptcy.

The ruling receives an abnormal amount of attention and is expected to have a significant impact on future public debt restructurings. For example, a WSJ article pointed out that "*there will*

1 See *UPIC & Co. v. Kinder-Care Learning Centers, Inc.*, 793 F. Supp. 448 (SDNY 1992); *YRC Worldwide Inc. v. Deutsche Bank Trust Co. Americas*, No. 10-2106-JWL, 2010 BL 149963, at (D. Kan. July 1, 2010); *In re Nw. Corp.*, 313 B.R. 595, 600 (Bankr. D. Del. 2004). However, in 1999, S.D.N.Y found a protective covenant-stripping exchange offer to violate the TIA because it violated the noteholders' practical ability to recover payments. See *Federated Strategic Income Fund v. Mechala Grp. Jamaica Ltd.*, No. 99 CIV 10517 HB, 1999 WL 993648 (SDNY Nov. 2, 1999).

be fewer indentures issued and more chapter 11 filings while this issue remains unresolved"[2]. Twenty-eight leading law firms pointed out in a legal opinion white paper that "*The EMC and Caesars cases have introduced interpretive issues that have disrupted established opinion practice.*" The EMC ruling thus plausibly represents an exogenous negative shock to the incidence and success rate of coercive bond exchange nationwide. It is a useful setting for testing the causal relation between coercive bond exchange offer (versus Chapter 11) and investment policy in a difference-in-difference-in-differences (DDD) framework. The DDD contrasts distressed firms with public debt to those without public debt and contrasts those before EMC to those after EMC. In January 2017, the Second Circuit Court of Appeals reverses the decision of the SDNY, thereby allowing for a second DDD test.

Consistent with the ruling representing a negative shock to out-of-court restructurings through coercive bond exchange offers, I find that, following the 2014 EMC ruling, a greater proportion of distressed firms with outstanding public debt file for Chapter 11. This trend is reversed after the 2017 EMC ruling. Also, stock returns (bond returns) of distressed firms respond negatively (positively) to the negative shock to coercive bond exchange offers. It suggests that out-of-court restructurings of public debt significantly increase shareholders' share of firm value at the expense of debtholder value (e.g., Gilson, John, and Lang, 1991; Franks and Torous, 1994).

To test the causal impact of restructuring method on investment, I compare distressed firms with outstanding public bonds under the TIA with those without outstanding public bonds under the TIA, before and after the EMC rulings. I first find that following the 2014 ruling that limits coercive exchange offers, affected distressed firms significantly reduce investment. The marginal effect is from -8% to -114% of the average investment ratio, depending on measurements of

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2 J. Scott Victor, 2015, *The Examiners: Practical Impairment Leads to Chapter 11*, *Wall Street Journal*

investment. The evidence is consistent with predictions by multiple theoretical papers (Myers, 1977; Gertner and Scharfstein, 1991; Favara, Morellec, Schroth, and Valta, 2017). Different theoretical papers generate the same prediction under different underlying mechanisms about the level of investment. To differentiate among these theoretical papers, I further investigate the change in investment efficiency. Investment efficiency (as measured by the sensitivity of investment to investment opportunities) of affected distressed firms significantly improves after the negative shock to coercive bond exchange. The result allows me to discriminate among the theoretical predictions and verify the analyses by Gertner and Scharfstein (1991) and Bernardo and Talley (1996). Following the 2017 ruling that facilitates coercive bond exchange offers, affected distressed firms respond oppositely (i.e., increase investment and reduce investment efficiency). Firms respond strongly to both EMC rulings if they have high renegotiation and bankruptcy costs, which are proxied by debt specialization.

In addition, ex-ante public debt contracting changes around the two EMC rulings. The results overall suggest that coercive debt exchange offers hurt bondholder wealth and increase required return, protective covenants, and new issues of bonds under the TIA. Offering yields of new debt issued under the TIA increase after the 2017 EMC decision. The number of protective covenants of new debt issued under the TIA decreases after the 2014 EMC decision and increases after the 2017 EMC decision. The number of new debts issued under the TIA also decreases after the 2014 EMC decision.

My paper supplements empirical research that compares out-of-court and in-court restructurings (e.g., Gilson, John, and Lang, 1991; Gilson, 1991, 1997; Franks and Torous, 1994; James, 1996). Previous papers investigate incentives and recovery rates of both solutions of distress but do not analyze the impact on corporate investment. It is also related to theoretical work examining the relation between public debt restructurings and investment (e.g., Gertner and Scharfstein, 1991; Mooradian, 1994; Asquith, Gertner, and Scharfstein, 1994; Bernardo and Talley, 1996; Bebchuk, 2002). To my knowledge, my paper provides direct evidence for this important causal relation for the first time. My research adds to the literature that tests the effect of out-of-court restructurings (versus Chapter 11) of public debt on shareholder and bondholder wealth (e.g., Kahan and Tuckman, 1993; Chatterjee, Dhillon, Ramirez, 1995; Lie, Lie, McConnell, 2001).

The research is also related to Denis and Wang (2014), who study the relation between private loan covenant renegotiations and investment[3]. Campello, Ladika, and Matta (2016) show that tax-induced reductions in out-of-court restructuring costs of syndicated loans lead to a significantly higher likelihood of debt renegotiations, measured by CDSs. Roberts and Sufi (2009) study renegotiations of private credit agreements between firms and financial institutions, which result in large changes to the amount, maturity, and pricing of the contract. My research contributes to the literature by studying out-of-court restructurings of public debt, in which traditional renegotiation between firms and lenders is difficult, and coercive debt exchange offer becomes an important tool. The coercive debt exchange offer is not often found in out-of-court restructurings of loans because loans are not subject to the TIA. Syndicated loans typically require the unanimous consent of all lenders, similar to the requirement of the TIA. Given syndicated loan ownership is relatively concentrated, the holdout problem is not severe and direct renegotiation is feasible. At the same time, syndicated loans are always senior secured, and firms are not able to use coercive exchange offers by issuing consenting debtholders more senior debt (Demiroglu and James, 2015).

3 Other papers about private loan renegotiation include Benmelech and Bergman (2008), Roberts and Sufi (2009), Nini, Smith, and Sufi (2009), Demiroglu and James (2015), etc.

The paper relates to an extensive literature that studies the effect of creditor rights on firm policies (e.g., Kalay, Singhal, and Tashjian, 2007; Acharya and Subramanian, 2009; Acharya, Amihud, and Litov, 2011; Favara, Schroth, and Valta, 2012; Vig, 2013; Hackbarth, Haselmann, and Schoenherr, 2015; Rodano, Serrano-Velarde, and Tarantino, 2016; Favara, Morellec, Schroth, and Valta, 2017; Mann, 2017; Suh, 2020). These studies use country-level indices of creditor rights (LLSV and DHMS) or use bankruptcy code reforms as shocks to creditors' bargaining power. None of these papers study relation between coercive bond exchange offers and investment, which have important economic and practical implications. Gertner and Scharfstein (1991) and Bernardo and Talley (1996) both theoretically study the conflict of interest between shareholders and bondholders in a setting of coercive exchange offer, generating predictions of the relation between coercive exchange offers and investment policies. Meanwhile, there is a long-standing debate about prudent legal reform of the TIA, and thereby out-of-court restructuring process of public debt. After the 2014 EMC decision impeded coercive exchange offer, Congress almost successfully amended the TIA in 2015 to facilitate coercive exchange offer. Gertner and Scharfstein (1991), Bernardo and Talley (1996), legal scholars, and professionals try to provide suggestions to the legal reform. However, none of the papers in the general creditor right literature contribute to this debate. My paper fills this gap by providing empirical evidence to Gertner and Scharfstein (1991) and Bernardo and Talley (1996), supporting their suggestions about legal reform related to out-of-court restructuring process of public debt.

2.2 Background and Related Theories of Out-of-court Restructurings of Public Debt

2.2.1 The Trust Indenture Act and Out-of-court Restructurings of Public Debt

Compared to in-court restructurings, out-of-court restructurings have lower direct costs and higher recovery rates for shareholders (e.g., Gertner and Scharfstein, 1991; Bernardo and Talley, 1996). Most firms would try to restructure their public and private debt out-of-court and only file for bankruptcy if they fail (Franks and Torous, 1994). Private loans and credit agreements are usually restructured out-of-court by directly renegotiating with creditors for their permission to cut repayment and extend maturity. Due to the Trust Indenture Act (TIA), public traded debts are usually restructured out-of-court through an indirect approach called coercive bond exchange offer.

Section 316(b) of the TIA states that "*the right of any holder of any indenture security to receive payment of the principal of and interest on such indenture security, on or after the respective due dates expressed in such indenture security… shall not be impaired or affected without the consent of such holder…*". The law prohibits directly amending core terms related to payments of public traded debt under the TIA, unless the amendment is approved by all of the debtholders. Because public debt is widely and dispersedly held, most firms cannot restructure public debts under the TIA (i.e., securities with an offering amount of $10 million or above[4]) by

4 Section 304 lists exemptions to the TIA. Main exemptions include: securities exempt from the Securities Act of 1933 (e.g., government securities, nonprofit organization securities, financial institutions, insurance or endowment policy, intrastate offerings, etc.), securities issued under a mortgage indenture as to which a contract of insurance under the National Housing Act is in effect, securities issued by a foreign government, securities issued otherwise than under an indenture, securities issued with aggregate principal amount of securities at any time outstanding thereunder to $10 million. Because I have excluded firms in banking, insurance, real estate, and trading sectors, remained US public firms have a low probability of qualifying for any exceptions, except for the $10 million offering

getting all of the bondholders' consent to relieve their debt burden. Instead, firms use exchange offers to restructure public debt outside of bankruptcy. In an exchange offer, a company makes an offer to bondholders to exchange cash or newly issued equity or debt securities (with more favorable terms to the debtor) for the outstanding bonds. Individual bondholders can choose from accepting the exchange offer and keeping the outstanding bonds. Exchange offers usually require the consent of bondholders of a minimum percentage of the total outstanding amount. The offer will be canceled without enough tendering bondholders.

However, a major obstacle to a successful public debt out-of-court restructuring is the holdout problem. Minority bondholders who reject the offer can receive full repayment after a successful exchange offer because tendering bondholders relieve firms' debt burden. If the benefits of rejecting the offer are more than savings in avoiding bankruptcy, then each minority bondholder will reject the offer and holdout. Holdout problems can impede bond exchange offers even though they are beneficial to shareholders and debtholders as a whole.

Two coercive techniques can be used to eliminate holdout problems. First, firms can offer to exchange original bonds for more senior or quickly maturing bonds. In default, tendering bondholders will receive payment before holdout bondholders do. Nevertheless, exchanging existing debts for senior debts is usually just a second-best solution. It does not completely relieve financial distress and is often prohibited by the underlying protective covenants (Roe, 1987). Second, exit consent, which is the focus of this paper, is a more coercive technique. Exit consent requires tendering bondholders to vote to remove non-core protective covenants prior to the exchange offer. If there are not enough tendering bondholders, then the exchange offer with exit

amount threshold. I simplify the procedure of identifying public debt under the TIA using the $10 million offering amount threshold.

consent is canceled. If there are enough tendering bondholders, then tendering bondholders exchange for new securities successfully. Holdout bondholders will continue to hold the original bonds. Although payment terms of the original bonds are intact, protective covenants are removed, causing holdout bondholders junior to tendering bondholders and reducing original bond values. Exit consent utilizes coordination costs among minority bondholders to create the prisoner's dilemma to force bondholders to accept an exchange offer, even though it is not in their collective interest to do so (Kahan and Tuckman, 1993).

2.2.2 Theories of Public Debt Restructuring Methods and Investment in Distressed Firms

In this section, I summarize the theories of in-court versus out-of-court restructurings of public debt and their implications for level and efficiency of investment. Some of the theories are general conflict between equityholders and debtholders in financial distress. Other theories are specifically about coercive bond exchange offer, which is a common way to restructure public debt out-of-court. Both strands of literature generate the same predictions about the effect of public debt restructuring on investment level. However, they lead to different predictions about the effect of public debt restructuring on investment efficiency.

2.2.2.1 The Effect of Out-of-court Restructurings of Public Debt on Investment in Distressed Firms

Out-of-court restructurings of public debt through coercive bond exchange offer could increase investment in distressed firms for several reasons. First, Myers (1977) indicates that distressed firms will underinvest when part of the benefits of new investment accrue to debtholders. The paper assumes that there is no deviation from absolute priority rules, i.e. creditors are paid off first. In reality, shareholders usually get paid before creditors are fully repaid both inside and outside of bankruptcy. Favara, Morellec, Schroth, and Valta (2017) extend Myers (1977) and set up a model that synthesizes debt overhang, risk-shifting, and debt enforcement in default. They predict that distortions in investment due to risky debt increase with debt enforcement. Because equity deviations from absolute priority are larger in coercive bond exchange offers than in Chapter 11 (Gilson, John, and Lang, 1990; Franks and Torous, 1993), coercive bond exchange offers eliminate the moral hazard underinvestment problem in distressed firms.

Second, Gertner and Scharfstein (1991) specifically predict the effect of out-of-court restructurings of public debt on investment in distressed firms. Firms use coercive techniques in exchange offers to strip seniority covenants that prohibit senior debt issues, or other protective covenants. The coercive technique allows firms to finish debt restructurings, reduce the burden of distress, and issue new senior debt to increase investment. However, it may reduce debt burden so much that overinvestment occurs.

2.2.2.2 The Effect of Out-of-court Restructurings of Public Debt on Investment Efficiency in Distressed Firms

All theoretical papers in Section 2.2.2.1 predict that out-of-court restructurings of public debt increase investment in distressed firms, but there are different predictions about whether they improve investment efficiency. The argument of Myers (1977) and Favara, Morellec, Schroth, and Valta (2017) suggests that out-of-court restructurings of public debt eliminate underinvestment. These studies thus predict that after a negative shock to out-of-court public debt restructuring through coercive bond exchange offers, distressed firms have lower investment efficiency.

By contrast, Gertner and Scharfstein (1991) and Bernardo and Talley (1996) suggest that distressed firms have higher investment efficiency after a negative shock to out-of-court public debt restructuring through coercive bond exchange offers. Gertner and Scharfstein (1991) directly discuss the effect of out-of-court restructurings on investment efficiency. The investment inefficiency emerges because the TIA practically disables firms from renegotiating directly with public debtholders. Although coercive bond exchange offer enables firms to circumvent the TIA and restructure public debt privately, it does not improve investment efficiency. The reason is that tendering and nontendering public debtholders are treated differently. The covenant stripping nature of exit consent might reduce too much of a firm’s debt burden, thereby allowing it to overinvest. Gertner and Scharfstein (1991) suggest repealing the TIA and allowing voting in public debt out-of-court restructurings (similar to the voting process in Chapter 11) because voting procedure treats consenting and dissenting bondholders equally and internalize the effects of the investment decision. It gets around the free-riding holdout and hold-in problems, thereby improving investment efficiency.

Bernardo and Talley (1996) predict that out-of-court public debt restructuring through coercive bond exchange reduces investment efficiency because it encourages managers to choose suboptimal ex ante investment projects to lower the expected payoff of holdout. Given fixed upside payoffs of an investment project, firms will choose projects with lower downside payoffs in the state of bankruptcy (payoffs in the bad state). It encourages bondholders to accept a poor exchange offer by reducing expected payoff of holdout. They suggest that under certain conditions, constraints on coercive bond exchange offers would be efficiency-enhancing.

2.3 Empirical Design

2.3.1 The Marblegate Asset Management et al. v. Education Management Corporation Ruling in 2014

As discussed in Section 2.2.1, Section 316(b) of the TIA prohibits formal amendments to the core terms related to payment amount and date without each bondholder's consent. The Second Circuit court and SDNY agree that Section 316(b) is ambiguous insofar as it "lends itself to multiple interpretations' that arguably favor either side on that issue". It is controversial whether it protects against "formal, explicit modification of the legal right to receive payment" or a much broader "practical ability" of a bondholder to receive payment.

Exit consent only impairs "non-core" terms (e.g. parent company guarantees, asset sales or transfers) with a majority creditor vote, while leaving "core" terms intact. Although exit consent effectively reduces value of bonds by removing protective covenants, it does not outwardly violate the TIA if the law is interpreted narrowly. The use of coercive bond exchange offers was rarely challenged after its use was upheld by the Delaware Court of Chancery in 1986[5].

However, the ruling of *Marblegate Asset Management et al. v. Education Management Corporation* in 2014 decreases expectations regarding the legal viability of coercive bond exchange offers. EMC proposes an exchange offer with exit consent, in which tendering creditors would consent to releasing parent company guarantee and transferring assets to a new subsidiary. The new subsidiary would issue equity to participating creditors and lead to an estimated 32.7%

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5 *Katz V. Oak Industries, Inc*. 508 A.2d 873 (Del.Ch. 1986)

recovery rate. The debtor would be left with no asset and dissenting creditors are expected to receive 0% recovery. The District Court for the Southern District of New York surprisingly concludes that EMC's proposed exit consent violates Section 316(b) of the Trust Indenture Act.[6] The SDNY interprets Section 316(b) of the TIA broadly that it not only prohibits formal amendment of core terms directly related to payment but also impairment to bondholders' practical ability to recover repayment.

The explanation soon disconcerted practitioners of troubled debt restructurings and was even considered the end of exit consent[7]. The 2014 EMC ruling could significantly affect out-of-court bond restructurings in ways favoring holdout creditors nationwide. The impact is not limited to NY or the Second Circuit District because creditors have incentives and abilities to engage in venue shopping to challenge exchange offers with exit consent in the SDNY regardless of the location of debtors. According to *stare decisis*, the SDNY is likely to adhere to its precedent. The TIA is a federal statute. Any claim under the TIA must be brought in a federal court, in which state of incorporation of bond issuers does not matter. For example, the EMC and Caesars Entertainment Corp neither locate headquarters nor incorporate in New York City. Creditors have a lot of latitude and incentives to follow the EMC case to have their cases heard in the SDNY for a more favorable judgment (e.g., *Gary Waxman and Leonard Hammerschlag, individually and on behalf a proposed class v. Cliffs Natural Resources Inc; Gregory Maniatis, individually and on behalf a proposed class v. Vanguard Natural Resources*). As the SDNY is one of the most influential and active federal district courts, other federal and state courts might follow the EMC ruling.

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6 Please see the Appendix for complete details of the proposed restructuring and the legal decision.

7 See, J. Scott Victor, 2015, *The Examiners: Practical Impairment Leads to Chapter 11*, *Wall Street Journal*. "*The recent cases in New York make it impossible to conduct an out-of-court restructuring without the consent of 100% of the affected noteholders. The only alternate to override the holdout noteholder is to have the issuer file for chapter 11 bankruptcy*".

The SDNY ruling was appealed to the Second Circuit Court of Appeals. It might limit my ability to detect real effects if managers expect that the case might be reversed. However, this only implies that my test results could underestimate the real effects but do not weaken my conclusions. Furthermore, distressed firms would still respond to the 2014 ruling for three reasons. First, most distressed firms were not able to postpone restructurings to 2017, when the next ruling was announced. They had to adhere to the 2014 ruling. Second, in January 2015, the court made a similar ruling in *MeehanCombs Global Credit et al. v. Caesars Entertainment Corp*, citing the EMC case. The Caesars case reinforced the impact of the 2014 EMC ruling in 10 trading days. Therefore, the effect of the 2014 EMC decision on investment is the synergy of both the 2014 EMC and the 2015 Caesars decisions. Third, event studies of stock and bond returns show that the market considered the ruling as a significant and unexpected event to distressed firms.

2.3.2 The Marblegate Asset Management et al. v. Education Management Corporation Ruling in 2017

To further address the concerns above, I use the ruling of the Second Circuit Court of Appeals as my second natural experiment. In January 2017, the Second Circuit Court of Appeals reversed the EMC decision by SDNY. The ruling implies that the TIA should be interpreted narrowly that a transaction is valid as long as it does not amend the core payment terms of the indenture. The Second Circuit Court's opinion reduces ambiguity in the application of Section 316(b) and litigation risk of future exit consent transactions. Using both the 2014 and 2017 EMC rulings as natural experiments to test the predictions helps to control for confounding effects. It considerably narrows the list of potential confounding events that would otherwise explain my results.

2.3.3 Media Coverage

Both rulings are unprecedentedly influential in business and legal professions in the area. Many business presses discussed the case, including WSJ, The New York Times, Reuters, Financial Times, Forbes, etc. There are 33 articles about the EMC case and 65 articles about the Caesars case in LexisNexis (116 and 138 in Factiva). In 2016, 28 leading law firms published a legal opinion white paper to provide guidance to practitioners in their consideration of the EMC and *Caesars* cases. They pointed out that "*The EMC and Caesars cases have introduced interpretive issues that have disrupted established opinion practice.*"

2.3.4 Validation of the Exogenous Shocks

In this section, I show that the 2014 and 2017 EMC decisions significantly affect the public debt restructuring process. First, I summarize the frequency of bankruptcy by year. Second, I conduct event studies of stock and bond returns around both decisions.

2.3.4.1 Frequency of Bankruptcy

After a negative shock to coercive bond exchange, affected distressed firms are less able to solve holdout problems in out-of-court debt restructurings. Thus, they are more likely to end up in bankruptcy courts. I justify the assumption that the EMC rulings have significant impacts on the in-court versus out-of-court restructuring of public debt. Table 2.1 summarizes Chapter 11 filings of distressed firms with and without public debt under the TIA by year. A firm is defined as a distressed firm if the default probability at the beginning of the year is in the top 20 percentile.

Next, I identify distressed firms that filed for Chapter 11 from 2013 to 2018 using UCLA-LoPucki Bankruptcy Research Database.

[Insert Table 2.1]

Column 1 of Table 2.1 lists the number of distressed firms by year. Columns 2 and 5 include distressed firms with and without public debt. Columns 3 and 4 (6 and 7) report the number and frequency of Chapter 11 filings among distressed firms with (without) public debt. From 2013 to 2018, 5.14% of the treated distressed firms filed for bankruptcy, while 5.53% of the control distressed firms filed for bankruptcy. In average, firms with and without public debt have similar frequencies of bankruptcy filings.

The frequency of Chapter 11 filings among treated distressed firms is relatively low at 0% - 2% in 2013-2014. Before the negative shock to coercive bond exchange offers, distressed firms can easily restructure public debt out-of-court and avoid bankruptcy. After the 2014 EMC decision, the percentage of bankruptcy filings among treated distressed firms increases. Although only 0% of treated distressed firms file for Chapter 11 in 2015, the percentage boosts to 13% in 2016. The ratio increases one year after the EMC decision potentially because many distressed firms first attempt to restructure debt out-of-court before filing for bankruptcy. Therefore, it takes months before affected firms start filing for bankruptcy. After the 2017 EMC decision, the percentage of bankruptcy filing among treated distressed firms gradually declines from 11% to 2%. It suggests that more distressed firms manage to restructure public debt out-of-court and avoid bankruptcy. In contrast, the frequency of bankruptcy filings among distressed firms without public debt remains stable from 5% to 8% around the two rulings. The two decisions have a weak effect on the restructuring process of distressed firms without public debt.

2.3.4.2 Shareholder Wealth Effect

To provide evidence that the rulings are influential and not perfectly anticipated, I turn to event studies of stock returns. Meanwhile, stock CARs show the welfare effect of public debt restructuring methods on shareholders. A negative shock to out-of-court public debt restructurings via coercive bond exchange offers should have a negative effect on shareholders' wealth. Gilson, John, and Lang (1991) show that stockholders seldom file for Chapter 11 without first attempting to restructure debt out-of-court. Franks and Torous (1994) find that shareholders have higher recovery rates in out-of-court restructurings. The shock reduces options available to managers in debt restructurings, and thus, their ability to maximize shareholders' wealth.

It is possible that investors are able to predict both EMC rulings before they are officially announced. I search for relevant events before December 30, 2014. On December 16, 2014, the SDNY denied the motion filed by Marblegate Asset Management seeking to preliminarily enjoin the Company from consummating its proposed debt restructuring. The judge also suggested on a preliminary basis that she agreed with the plaintiffs' claim. However, her opinion was under seal until December 30, 2014, making it unclear whether the fight over the violation of the act will land. So, the information disclosed on December 16, 2014 is mixing. The oral argument of the 2017 EMC decision was heard on May 12, 2016. However, there is no clear clue about the ruling.

The sample is limited to treated firms, i.e., as of November 30th, 2014 (December 31st, 2016), firms have outstanding public bonds under the TIA with maturity date after December 31st, 2016 (December 31st, 2018). I group firms into distressed and non-distressed groups. Distressed firms are those with top quintile default probability in November 2014 (December 2016). CARs of stocks are calculated using the Fama-French three-factor model around the rulings (i.e., December 30th, 2014; January 17th, 2017). The estimation window is [-200, -50]. I report univariate test results of stock CARs of each group on the event day (day 0). To account for the possibility of information leakage prior to the event or a lag in the information being incorporated into prices, I also analyze CARs in progressively wider windows centered on the event date. Differences in CARs between distressed and non-distressed firms are reported, controlling for the within-industry and within-state correlations.

[Insert Table 2.2]

Panel A of Table 2.2 provides stock CARs around December 30th, 2014. Stock CARs in [-5,5] of firms with high default probabilities were significantly negative. This implies that a negative shock to out-of-court restructurings through coercive exchange offers reduces shareholder wealth. The negative shock to coercive debt exchange offers limits shareholders' ability to obtain concessions from bondholders and avoid costly bankruptcy. The effect is only significant in firms with high default probabilities because they are more likely to restructure their debt, and thus, affected by the ruling. Panel B of Table 2.2 includes a similar event study analysis on January 17th, 2017. Stock CARs of firms with high default probabilities around the 2017 EMC decision are significantly positive. The reverse of the 2014 ruling increases shareholder wealth in affected distressed firms. Overall, results in Table 2.2 indicate that firms' ability to restructure public debt out-of-court through coercive debt exchange offers increases shareholder value[8].

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8 Lie, Lie, and McConnell (2001) show that announcements of debt-reducing exchange offers are associated with a negative average stock price reaction. They argue that coercive bond exchange offer itself benefits shareholders because managers undertake debt-reducing exchange offers in an attempt to avoid bankruptcy and preserve value for shareholders. They explain that the negative stock return reaction is because the announcements also convey new information that the firms' financial situation is fragile. My paper is not at odds with their results. I document positive stock returns around a positive shock to firms' ability to use exchange offers. The shocks do not convey any negative information about individual firms. My results are, thereby, consistent with Lie, Lie, and McConnell (2001)' argument.

2.3.4.3 Bondholder Wealth Effect

The effect of a negative shock to out-of-court restructurings through coercive bond exchange offers on bond returns is unclear. On the one hand, bondholders will no longer be forced to accept exchange offers because they face the prisoner's dilemma in exit consent. Shareholders can no longer easily extract concessions and wealth from minority bondholders. On the other hand, holdout problems might impede restructurings and benefit strategic holdout creditors at the expense of the majority of creditors. An exchange offer that relieves the debt burden of a viable company and offers relatively better repayment to bondholders as a whole might be blocked by holdout problems. Whether bond return responds positively or negatively to a negative shock to coercive bond exchange offers is an empirical question, which depends on many factors, including coordination among bondholders, ownership structure, the prospect of debtor's financial health, and judicial protection of bondholders, etc. I use bond CARs of affected firms with different default probabilities to examine which of these two countervailing effects dominates.

I follow the five-factor model in Fama and French (1993) to estimate the response of bond return around the rulings. Bond CARs are estimated at the bond level. Estimating bond CARs is challenging because bonds are thinly traded. There are 3,855 unique firms (ticker) and 31,742 unique bonds (cusip) from 2014 to 2015, but only 892 firms (ticker) and 2,727 bonds (cusip) with trading data on December 30, 2014. There are 4,029 unique firms (ticker) and 35,377 unique bonds (cusip) from 2016 to 2017, while only 1,343 firms (ticker) and 5,112 bonds (cusip) with trading data on January 17, 2017. As a result, there are not enough data to analyze CARs in a narrow event window. I report CARs in a wide event window [-5, 5]. The estimation window is [-200, -50]. In equation (1), Rm – Rf, SMB, and HML are factors available at Kenneth French's website. Term is the slope of the Treasury yield curve, which is the difference between long-term government bond return (measured by SPDR Portfolio Long Term Treasury ETF (TLO)) and the one-month Treasury bill rate. Def is the difference between the returns on long-term corporate bond indices (measured by SPDR Bloomberg Barclays Long Term Corporate Bond ETF (LWC)) and long-term Treasuries (measured by SPDR Portfolio Long Term Treasury ETF (TLO)). $R_{i,t}$ is bond-level return calculated as price in t divided by price in t-1 minus 1, using daily weighted average bond transaction price in TRACE.

$$R_{i,t} - Rf_t = b_0 + b_1(Rm_t - Rf_t) + b_2SMB_t + b_3HML_t + b_4Term_t + b_5Def_t + \varepsilon_{i,t} \quad (1)$$

Table 2.3 Panel A reports bond CARs of treated firms around December 30, 2014. CARs of treated firms with high default probabilities were significantly positive. Differences in bond CARs between high and low default probability groups are significantly positive. In Table 2.3 Panel B, the positive shock to coercive exchange offers on January 17, 2017 results in negative bond CARs in treated firms with high and low default probabilities. The magnitude of negative bond CARs in the high default probability group is significantly larger. Results in Table 2.3 imply that coercive bond exchange offers could transfer wealth from bondholders to shareholders and hurt bondholders' collective interests.

[Insert Table 2.3]

Kahan and Tuckman (1993)'s model predicts that exchange offers with exit consent hurt bondholders because they may consent to coercive exchange offer even when it is not in their collective interest to do so. However, they find that bondholder returns around coercive bond exchange offer announcements are positive. They explain that bondholders coordinate their actions to modify or defeat disadvantageous proposals and therefore can demand some of the gains resulting from exit consent. By studying bond returns around exogenous shocks to firms' ability to use exit consent instead of coercive bond exchange offer announcements, I find supporting evidence for Kahan and Tuckman (1993)'s model.

2.4 Results

2.4.1 Descriptive Statistics

I collect quarterly financial reporting data from Compustat and daily stock return data from CRSP, excluding firms in the financial sector (SIC 6000-6999). Data of corporate bonds is obtained from Capital IQ. Panel A of Table 2.4 reports summary statistics of dependent and independent variables for the full sample from 2013 to 2018. I also report firm characteristics of treated and control subsamples around the 2014 and 2018 rulings in Panel B & C. In the 2014 EMC ruling, $Treat_i$ is a dummy variable, which equals one if, as of November 30, 2014, firm i has outstanding public bonds under the TIA (i.e., securities with an offering amount of $10 million or above) with maturity date after December 31, 2016. The sample period is from 2013 to 2016. In the 2017 EMC ruling, $Treat_i$ equals one if, as of December 31, 2016, firm i has outstanding public bonds under the TIA with the maturity date after December 31, 2018. The sample period is from 2015 to 2018.

Investment is measured as Capex in quarter t, scaled by total assets (At) in quarter t-1[9]. Asset growth is the growth rate in At from t-1 to t. R&D is calculated as Xrd/At. Missing Xrd is set to zero. Return on assets (ROA) is calculated as net income divided by total assets. ROA volatility is

9 Compustat quarterly data reports cumulative Capex through each given quarter. Therefore, Capex in quarter t should be $Capex_t$-$Capex_{t-1}$, expect for the first quarter in each fiscal year.

the standard deviation of ROA in the previous eight quarters. Equity volatility is the standard deviation of weekly return in quarter t. Leverage is defined as long-term debt plus current liability, divided by total assets ((Dltt+Dlc)/At). Depreciation is scaled by total assets. Tobin's q is (At+Prcc×Csho-Ceq)/At. Default probability is calculated using the Merton distance-to-default model in the month prior to the rulings, based on Bharath and Shumway's SAS code (Bharath and Shumway, 2008). I winsorize all continuous variables at the 1% and 99% levels.

Table 2.4 shows that treated and control firms are significantly different in several firm characteristics. Treated firms have higher leverage, larger size, higher stock return, relative to control firms. Control firms have higher Tobin's q than treated firms. I control for these variables and firm fixed effects to make sure that observable and unobservable differences are not driving the results. Furthermore, courts' decisions are independent of differences between treated and control firms. The DDD setting allows me to identify the causal relation between restructuring methods of public debt and investment. To further address for this concern, I conduct a propensity score matching and difference-in-differences (PSM-DID) analysis in Section 2.6.6.

[Insert Table 2.4]

2.4.2 Investment

As discussed earlier, many theoretical papers make predictions about effects of restructuring methods of public debt on investment (e.g., Myers, 1977; Gertner and Scharfstein, 1991; Favara, Morellec, Schroth, and Valta, 2017). To test this important causal relation, I follow Becker and Stromberg (2012) and Favara, Morellec, Schroth, and Valta (2017) and use two DDD analyses. In the first DDD analysis of the 2014 EMC ruling, my sample period is from 2013 to 2016 because the ruling was reversed in January 2017. As the 2014 EMC and 2015 Caesars decisions are a succession of negative shocks to coercive debt exchange offers, the first DDD analysis tests the effect of both rulings. In equation (2), the dependent variables are Capex scaled by total assets, asset growth, and R&D scaled by total assets. $Treat_i$ is a dummy variable, which equals one if, as of November 30, 2014, firm i has outstanding public bonds under the TIA (i.e., securities with an offering amount of $10 million or above) with maturity date after December 2016. Aft_t is a dummy variable, which equals one after 2014. $Distress_i$ is a dummy variable, which equals one if firm i's default probability in November 2014 is in the top quintile. Default probability is calculated using the Merton distance-to-default model. Control variables include ROA, ln(Total assets), ln(Sales), ln(Equity market value), Depreciation over total assets, Leverage, Two-quarter stock price change, and Tobin's q. All control variables are at the end of quarter t-1. I control for firm fixed effects and quarter fixed effects. I also follow Becker and Stromberg (2012) to cluster standard errors by the interaction of a firm's state of incorporation and quarter. $Treat_i \times Distress_i$, $Treat_i$, Aft_t, and $Distress_i$ are dropped after including firm fixed effects because of collinearity. $Treat_i \times Distress_i \times Aft_t$ is the parameter of interest. Because I control for $Treat_i \times Aft_t$ and $Distress_i \times Aft_t$, $Treat_i \times Distress_i \times Aft_t$ measures the marginal effect of the shocks on investment in distressed firms with outstanding public debt relative to firms with outstanding public debt and firms with high default probabilities.

$$\begin{aligned}\mathrm{Investment}_{i,t} = {} & b_0 + b_1 \mathrm{Treat}_i * \mathrm{Aft}_t * \mathrm{Distress}_i + b_2 \mathrm{Treat}_i * \mathrm{Aft}_t + b_3 \mathrm{Aft}_t * \mathrm{Distress}_i \\ & + b_{control} \mathrm{Controls}_{i,t-1} + \mu_t + \alpha_i + \varepsilon_{i,t} \qquad (2)\end{aligned}$$

In the second DDD analysis, I use equation (2) to test the effect of the 2017 EMC ruling on investment. The sample period is 2015 – 2018. $Treat_i$ equals one if, as of December 31, 2016, firm i has outstanding publicly traded debt under the TIA with the maturity date after December 31,

2018. $Distress_i$ is defined using default probability in December 2016. Aft_t is a dummy variable, which equals one after 2016. Other variables remain the same as in the first DDD.

The DDD analyses provide a clean setting to test the causal relation because the three dummy variables capture different characteristics. $Treat_i$ identifies whether a firm has outstanding public debt under the TIA. It might be related to firm size because firms with public debt tend to be large firms. To make sure that firm size is not driving the result, I control for it in regressions. $Distress_i$ is significantly different from $Treat_i$. Firms with outstanding public debt are not necessarily distressed. Meanwhile, distressed firms are not necessarily affected by the treatment as long as they do not have outstanding debt under the TIA.

2.4.2.1 The Parallel Trend Assumption

A core assumption of DDD is that there is no pre-existing differential trend between treated and control firms. Under this assumption, any difference after the treatment is the result of the treatment. The absence of pre-treatment parallel trend leads to biased estimates of the causal effect. Panel A of Figure 2.1 shows the parallel trend of capital expenditure ratios of treated and control groups in distressed firms around the 2014 EMC ruling. The event date t=0 is 2014Q4. I plot the quarter-by-quarter differences in capital expenditure of treated distressed and control distressed firms relative to those in 2013Q1 ($t = -7$). Prior to the 2014 EMC ruling, both groups had similar trends. The average differences in capital expenditure ratio between treated distressed and control distressed firms are not statistically different from those in 2013Q1. After the 2015Q2 (t=2), the average differences become significantly lower than those in 2013Q1. There is a two-quarter lag in adjustment of investment. Figure 2.1 supports the pre-treatment parallel trend assumption of DDD analysis.

Panel B of Figure 2.1 shows the parallel trend of capital expenditure ratios of treated and control groups in distressed firms around the 2017 EMC ruling. The event date t=0 is 2017Q1. Because the 2014 EMC ruling happened in December 2014 ($t = -9$), the pre-treatment trend is not perfectly parallel. Differences in capital expenditure of treated distressed and control distressed firms keep decreasing after 2015Q1 ($t = -8$). The trend was reversed three quarters after the 2017 EMC ruling (t=3) as the difference in capital expenditure after 2017Q4 increases back to the level in 2015Q1.

[Insert Figure 2.1]

2.4.2.2 Difference-in-Difference-in-Differences Analysis

Table 2.5 presents the results of investment in the 2014 EMC ruling. Coefficients of $Treat_i \times Post\text{-}2014_t \times Distress_i$ are significantly negative in regressions of capital expenditure ratio, asset growth, and R&D. After the 2014 EMC ruling reduces treated firms' ability to use coercive bond exchange offers in out-of-court restructurings, investment decreases in distressed firms. The marginal effect in the regression of capital expenditure ratio is -0.004, which is 31% of the average investment ratio. The marginal effect on asset growth in distressed firms is -0.024, which is 114% of the average asset growth. The marginal effect on R&D in distressed firms is -0.001, which is 8% of the average R&D. Table 2.5 shows that a negative shock to coercive bond exchange offers in out-of-court restructurings drastically reduces investment in distressed firms. The result provides empirical support for both Myers (1977) and Gertner and Scharfstein (1991). However, it does not distinguish these two different mechanisms, i.e., decrease or increase agency costs of debt. To answer this question, I will study investment efficiency in Section 2.4.3.

[Insert Table 2.5]

Table 2.6 tabulates the results for investment in the 2017 EMC ruling. It confirms the conclusion in Table 2.5. Coefficients of $Treat_i$ × Post-2016_t × $Distress_i$ are significantly positive in regressions of capital expenditure ratio and R&D. The marginal effects are 0.002/0.013=16% of the average capital expenditure ratio and 0.002/0.012=17% of the average R&D ratio. After the 2017 EMC ruling enabled treated firms to conduct coercive bond exchange offers, distressed firms increased investment.

[Insert Table 2.6]

2.4.3 Investment Efficiency

Contrary to Myers (1977), Gertner and Scharfstein (1991) and Bernardo and Talley (1996) predict that coercive debt exchange is negatively related to investment efficiency. To differentiate these predictions, I study the effect of the rulings on investment efficiency. I follow Badertscher, Shroff, and White (2013) to use the sensitivity of investment to investment opportunities as a proxy for investment efficiency. Investment opportunities are measured by Tobin's q or Sales growth. Tobin's q is calculated as (At+Prcc×Csho-Ceq)/At. Sales growth in t is $(Sale_t - Sale_{t-1})/Sale_{t-1}$. The high sensitivity of investment to investment opportunities implies that the firm makes efficient investment decisions because it is more responsive to increases in investment opportunities. A significantly positive coefficient of $Treat_i$ ×Aft_t × $Distress_i$ × Investment $opportunities_{i,t-1}$ in equation (3) suggests that the shock improves investment efficiency in affected distressed firms, and vice versa. Control variables include ROA, ln(Total assets), Leverage, Cash holdings, and Investment opportunities. All control variables are at the end of quarter t-1. $Treat_i$×$Distress_i$, $Treat_i$, Aft_t, and $Distress_i$ are dropped after including firm fixed effects because of collinearity. Because I control for $Treat_i$×$Distress_i$ × Investment $opportunities_{i,t-1}$, Aft_t × $Distress_i$ × Investment opportunities$_{i,t-1}$, Treat$_i$ × Investment opportunities$_{i,t-1}$, Aft$_t$ × Investment opportunities$_{i,t-1}$, Distress$_i$ × Investment opportunities$_{i,t-1}$, and Investment opportunities$_{i,t-1}$, the coefficient of Treat$_i$ ×Aft$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$ captures the marginal effect of the shocks on investment efficiency in distressed firms with outstanding public debt relative to distressed firms and firms with outstanding public debt.

$$\begin{aligned}\mathrm{Investment}_{i,t} = {} & b_0 + b_1\mathrm{Treat}_i * \mathrm{Aft}_t * \mathrm{Distress}_i * \mathrm{Investment\ opportunities}_{i,t-1} + b_2\mathrm{Treat}_i * \mathrm{Aft}_t \\ & * \mathrm{Investment\ opportunities}_{i,t-1} + b_3\mathrm{Aft}_t * \mathrm{Distress}_i * \mathrm{Investment\ opportunities}_{i,t-1} \\ & + b_4\mathrm{Treat}_i * \mathrm{Distress}_i * \mathrm{Investment\ opportunities}_{i,t-1} + b_5\mathrm{Aft}_t \\ & * \mathrm{Investment\ opportunities}_{i,t-1} + b_6\mathrm{Treat}_i * \mathrm{Investment\ opportunities}_{i,t-1} + b_7\mathrm{Distress}_i \\ & * \mathrm{Investment\ opportunities}_{i,t-1} + b_8\mathrm{Treat}_i * \mathrm{Aft}_t * \mathrm{Distress}_i + b_9\mathrm{Treat}_i * \mathrm{Aft}_t + b_{10}\mathrm{Aft}_t \\ & * \mathrm{Distress}_i + b_{control}\mathrm{Controls}_{i,t-1} + \mu_t + \alpha_i + \varepsilon_{i,t} \qquad (3)\end{aligned}$$

Table 2.7 shows the estimates of the effect of the 2014 EMC ruling on investment efficiency. Investment opportunities$_{i,t-1}$ is Tobin's q$_{i,t-1}$ in Column 1 and Sales growth$_{i,t-1}$ in Column 2. In Column 1, coefficient of Treat$_i$ × Post-2014$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$ is 0.003 (P-value=0.154). In Column 2, the coefficient of Treat$_i$ × Post-2014$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$ is significantly positive. Table 2.7 shows that a negative shock to coercive bond exchange offers in out-of-court restructurings has a positive effect on investment efficiency. It is consistent with Gertner and Scharfstein (1991) and Bernardo and Talley (1996) that out-of-court restructuring of public debt through coercive debt exchange offers might lead to investment inefficiency.

[Insert Table 2.7]

Table 2.8 includes results of investment efficiency in the 2017 EMC ruling. The coefficient of Treat$_i$ × Post-2016$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$ is significantly negative in column 1. The treatment has a negative effect on the sensitivity of investment to investment opportunities.

Investment efficiency decreased in distressed firms after the 2017 ruling allows firms to utilize coercive bond exchange offers again. Table 2.8 supports the results in Table 2.7.

[Insert Table 2.8]

Results of the sensitivity of investment to investment opportunities might be biased because investment opportunities are measured with error (e.g., Erickson and Whited, 2000). Following Badertscher, Shroff, and White (2013) and Asker, Farre-Mensa, and Ljungqvist (2014), I use changes in state corporate income tax rates as exogenous shocks to investment opportunities. A decrease in state tax could increase firms' after-tax return on investment, and thus investment opportunities. Investment $\text{opportunities}_{i,t-1}$ equals 1 (-1) if firm i is headquartered in a state with a decreasing (increasing) tax rate. Investment $\text{opportunities}_{i,t-1}$ equals 0 if firm i is headquartered in a state with a constant tax rate. Other variables remain the same as in equation (3). In unreported test results, b_1 is 0.016 (P-value=0) in the 2014 ruling. b_1 is insignificantly different from zero in the 2017 ruling. Overall, the inferences from Table 2.7 & 2.8 are largely unchanged.

2.5 Additional Results

The results in section 2.4 indicate that after a negative shock to coercive debt exchange offers, investment decreases, while risk-taking and efficiency increase. The rulings significantly change the bargaining power and wealth allocation of shareholders and bondholders. Thus, the shocks might affect ex-ante public debt contracting. I study changes in costs of debt financing, bond covenants, and debt issuance frequency after the shocks. The overall welfare effect is studied. I also compare the main test results of firms with high and low renegotiation and bankruptcy costs as measured by debt specialization.

2.5.1 Costs of Debt Financing Under the TIA

I first study the ex-ante effect of the rulings on offering yields of newly issued debt under the TIA. There is no clear prediction for the relation. The 2014 EMC ruling might increase public debtholder protection and reduce costs of public debt financing. However, if the 2014 EMC ruling increases agency costs of debt, then creditors will require higher costs of debt. A similar analysis applies to the 2017 EMC ruling.

I obtain issuance data of corporate public debts in 2013 – 2018 from Capital IQ (debentures and medium-term notes), including covenants, offering amount, maturity date, and offering yield. I conduct a difference-in-differences analysis of offering yields around the rulings. The dependent variable is Ln(Offering yield+1). Above_$10 million$_j$ is a dummy variable, which equals one if offering amount of bond j is more than $10 million. Bond j is subject to the TIA if Above_$10 million$_j$ equals one. In Table 2.9 Column 1, I report the regression result of offering yield around the 2014 EMC ruling, using data of newly issued bonds in 2013 - 2016. The coefficient of Above_$10 million$_j$ × Post-2014$_t$ is insignificantly different from zero. This implies that costs of debt financing do not change after a negative shock to coercive debt exchange offers. Column 2 shows the change in offering yields of public bonds issued in 2015-2018 around the 2017 EMC ruling. The positive coefficient of Above_$10 million$_j$ × Post-2016$_t$ implies that after a positive shock to coercive debt exchange, offering yields increase. The marginal effect is $e^{0.092}-1=9.6\%$. This weakly supports the argument that coercive debt exchange offers hurt bondholder wealth and increase the required return of bonds under the TIA.

[Insert Table 2.9]

2.5.2 Covenants of New Debt Issues

I test the ex-ante effect of the EMC rulings on protective covenants of new debt issues under the TIA. Strong judicial protection reduces bondholders' reliance on debt covenants. Therefore, I expect a decrease (increase) in the number of covenants of public debt under the TIA, after the 2014 (2017) EMC ruling.

Table 2.10 tabulates difference-in-differences analysis of debt covenants around the EMC rulings. The dependent variable is Ln(Number of bondholder protective and issuer restrictive covenants+1). Above_$10 million$_j$ is a dummy variable, which equals one if offering amount of bond j is more than $10 million (subject to the TIA). Column 1 shows the regression of the number of protective covenants around the 2014 EMC ruling, using data of newly issued bonds in 2013 - 2016. The negative coefficient of Above_$10 million$_j$ × Post-2014$_t$ implies that the number of covenants decreases for new debt issued under the TIA after 2014. Bondholders rely less on protective covenants after a negative shock to coercive bond exchange offers. The marginal effect is $e^{0.13}$-1 = -0.138. Column 2 includes changes in the number of bond covenants of new debt issued in 2015-2018 around the 2017 EMC ruling. Consistent with Column 1, the positive coefficient of Above_$10 million$_j$ × Post-2016$_t$ means that bondholders increase protective covenants when firms can use coercive techniques to force them to consent to unfair exchange offers. The marginal effect is $e^{0.189}$-1=0.21.

[Insert Table 2.10]

2.5.3 Number of New Debt Issues

I study the ex-ante effect of the rulings on the number of newly issued debts under the TIA. Affected firms have incentives to avoid issuing new debts under the TIA after the 2014 EMC ruling as it facilitates holdout. An increase in the total number of debtholders will increase the probability of the existence of holdout creditors. A large number of different public debt securities could make the debt structure less concentrated and more complex. As a result, disagreement and holdout problems are serious, and thereby it is difficult to restructure public debt out-of-court (Gilson, John, and Lang, 1990). Therefore, I expect that affected and distressed firms will reduce the number of new debts issued under the TIA after the 2014 EMC ruling.

Table 2.11 lists the results of the number of new debts under the TIA around the 2014 (Column 1) and 2017 (Column 2) EMC decisions. The dependent variable is Ln(Number of new debts under the TIA + 1)$_{i,t}$. Number of new debts under the TIA is the number of new public debts offered by firm i in quarter t with offering amount above \$10 million. In Column 1, $Treat_i \times Post\text{-}2014_t \times Distress_i$ is significantly negative, which shows that affected and distressed firms issue less new debts under the TIA after a negative shock to coercive debt exchange offer. In Column 2, $Treat_i \times Post\text{-}2016_t \times Distress_i$ is insignificantly different from zero. Results in Table 2.11 weakly support that when holdout problem becomes more severe, firms issue less new debts under the TIA to facilitate out-of-court restructurings.

[Insert Table 2.11]

2.5.4 Debt Specialization

Debt concentration lowers negotiation and bankruptcy costs (e.g., Bolton and Scharfstein, 1996; Ivashina, Iverson, and Smith, 2011; Colla, Ippolito, and Li, 2013). Firms with high expected bankruptcy costs should have specialized ex-ante debt structure to reduce renegotiation costs. Although specialized debt structure makes renegotiation in-court and out-of-court easier, the 2014 EMC decision makes it easier for a minor holdout bondholder to block out-of-court restructuring. So, firms that choose ex-ante concentrated debt structure are more vulnerable to the 2014 EMC decision and will respond more strongly to the events. I follow Colla, Ippolito, and Li (2013) to compute a normalized Herfindahl-Hirschman Index (HHI) of debt type usage. CP, DC, TL, SBN, SUB, CL, Other, and TD refer to commercial paper, drawn credit lines, term loans, senior bonds and notes, subordinated bonds and notes, capital leases, other debt, and total debt. Higher HHI values indicate specialized debt structures.

$$Debt\ HHI_{i,t} = \frac{(\frac{CP_{i,t}}{TD_{i,t}})^2+(\frac{DC_{i,t}}{TD_{i,t}})^2+(\frac{TL_{i,t}}{TD_{i,t}})^2+(\frac{SBN_{i,t}}{TD_{i,t}})^2+(\frac{SUB_{i,t}}{TD_{i,t}})^2+(\frac{CL_{i,t}}{TD_{i,t}})^2+(\frac{Other_{i,t}}{TD_{i,t}})^2-\frac{1}{7}}{\frac{6}{7}} \qquad (4)$$

Table 2.12 presents the evidence of investment policies with different debt specialization. Panel A shows the changes in investment policies around the 2014 EMC decision, and Panel B includes those around the 2017 EMC decision. Debt Specialization$_i$ equals one if firm i has top 20% Debt HHI in 2014Q4 or 2016Q4. Treat$_i$, Post-2014$_t$, Post-2016$_t$, and Distress$_i$ are the same as in previous tables. Consistent with Table 2.5 and 2.6, coefficients of Treat$_i$ × Post-2014$_t$ × Distress$_i$ in Panel A are negative in regressions of investment. Treat$_i$ × Post-2014$_t$ × Distress$_i$× Debt Specialization$_i$ is also negative in regressions of investment, suggesting that firms with specialized ex-ante debt structure respond more strongly to the 2014 EMC decision. Treat$_i$ × Post-2014$_t$ × Distress$_i$ × Debt Specialization$_i$ ×Tobin's q$_{i,t-1}$ is significantly positive in the regression of investment. This implies that investment efficiency improves only in firms with specialized debt structure. The evidence is confirmed by Panel B because firms respond oppositely to the 2017 EMC decision. Overall, firms with high negotiation and bankruptcy costs respond more strongly to both EMC decisions.

[Insert Table 2.13]

2.6 Robustness Analysis

In this section, I report the results of several tests of whether my primary findings are robust to choosing an alternative event date as a placebo and alternative measures of distress. I also control for regional economic conditions and cluster standard errors at a different level. For the sake of briefness, these results are mostly not tabulated.

2.6.1 Placebo tests

I conduct a placebo test using any quarter from 2013Q3 to 2014Q3 as the treatment date, with the same treated and distressed groups. I exclude data after 2015Q1 when running placebo DDD tests. None of the variables of interest is significant in regressions of investment. Except that when the treatment date is set to 2014Q3, the variable of interest in the regression of capital expenditure ratio is 0.002 (P-value = 0.064).

2.6.2 Alternative measurements of financial distress

I use Gilson, John, and Lang (1990)'s method to define distressed firms. I started with firms with quarterly stock returns that are ranked in the bottom 30% of the CRSP universe at the end of 2014Q4 or 2016Q4. Firms with leverage higher than 20% are distressed firms. Overall, I obtain similar results, except that the marginal effect on investment efficiency around the 2014 ruling is insignificant. The marginal effect on risk-taking around the 2017 ruling is positive.

Another concern is that the binary cutoff of distress is subjective. In the main tests, firms in the top quintile default probability in November 2014 and December 2016 are labeled distressed firms. However, managers might define distress using a different cutoff or in a gradual fashion. I replace the binary variables $Distress_i$ with default probabilities in November 2014 and December 2016, which are continuous variables. Implications of DDD tests are similar to those of main tests, except for results of investment efficiency in the 2017 ruling are insignificant.

Defining financial distress using default probabilities right before the treatment (November 2014 and December 2016) might distort estimations. I use default probabilities prior to the sampling period (December 2012 and December 2014) to measure financial distress. Conclusions from regressions of investment and investment efficiency do not change, except for results of investment in the 2017 ruling.

2.6.3 Difference-in-differences analyses

I use DDD analyses to test hypotheses in the main tests. To simplify the tests, I use DID analyses as robustness tests. First, I estimate the effects of $Treat_i \times Aft_t$ for firms with high default probabilities. Regressions of investment and investment efficiency of the 2014 and 2017 EMC rulings generate consistent results. Second, I estimate the effects of $Distress_i \times Aft_t$ for firms with outstanding public debt under the TIA. Most results are consistent with main tests. However, coefficients of $Distress_i \times Aft_t$ become insignificant in regressions of investment efficiency in the 2017 EMC decision. Overall, results of DID analyses are similar to results of DDD analyses.

2.6.4 Fixed effects and standard errors

To control for the effect of regional business cycles on investment, I include Headquarter state × Quarter fixed effects in main specifications. Results are similar to those in baseline regressions, except results of investment efficiency in 2017 are insignificant. I also calculate standard errors by clustering at the firm level. Most conclusions do not change, except that variables of interest in investment and efficiency regressions of the 2017 EMC ruling become insignificant.

2.6.5 Trends of firm characteristics that are related to debt restructurings

Changes in firm characteristics around the EMC rulings might drive restructuring process of distressed firms. To exclude this alternative explanation, I show differential trend between treated distressed and control distressed firm characteristics around the 2014 EMC decision. Bank debt/Total debt and Intangible assets/Total assets are two important determinants of restructuring methods (Gilson, John, and Lang, 1990). In Figure 2.2 and 2.3, I plot the quarter-by-quarter differences in Bank debt/Total debt and Intangible assets/Total assets of treated distressed and control distressed firms relative to those in 2013Q1 ($t = -7$). Figure 2.2 shows that differences in bank debt ratio of treated distressed and control distressed firms are significantly lower than those in 2013Q1. However, the differences are generally stable during the sample period. Figure 4 shows that differences in Intangible assets/Total assets of treated distressed and control distressed firms from 2013Q2 to 2016Q4 are insignificantly different from that in 2013Q1. Both differences in Bank debt/Total debt and differences in Intangible assets/Total assets are stable around 2014Q4. Therefore, the rulings instead of changes in firm characteristics are driving the main results.

[Insert Figure 2.2 and Figure 2.3]

2.6.6 Propensity score matching and difference-in-differences

Being a firm with and without public debt subject to TIA is not random. This raises the probability that the findings are driven by factors correlated with choice of public debt. Moreover, Table 2.4 shows that firms with and without public debt under the TIA have different characteristics, such as Leverage, Ln(Market value of equity), and Ln(Sale). I use propensity score matching and difference-in-differences (PSM-DID) to make sure that treated and control firms are similar and comparable. First, I conduct one-to-one propensity score matching with replacement. I estimate propensity score using logistic regression according to ROA, leverage, size, Tobin's q, ROA volatility, PPENT, rating, and investment grade before the rulings (rating and investment grade in 2016Q4 are not included in the estimation of 2017 because Compustat S&P Ratings database in WRDS has been discontinued). Second, I use the treated and matched control groups to conduct similar DID analyses. Table 2.14 reports the summary statistics of treated and control firms of both rulings after matching. Treated and matched control groups are similar in most firm characteristics in both the 2014 and 2017 EMC decisions. Table 2.15 tabulates main test results estimated using matching samples. The sample of tests of level and risk of investment are limited to distressed firms. Consistent with results in Table 2.5 – 2.8, treated distressed firms reduce (increase) investment and increase (reduce) volatilities after the 2014 (2017) EMC ruling. The magnitudes of coefficients remain similar to those in main tests. P-value of some coefficients are slightly above 0.1. In Column 2 of Panel A, the P-value of coefficient -0.021 is 0.163. In Panel B, the P-value of coefficient 0.002 is 0.167, and the P-value of coefficient 0.004 is 0.186. Although the results are weaker than those of main test, they still have similar implications. Similar to Table 2.7 and 2.10, coefficients of $Treat_i \times Post\text{-}2014_t \times Distress_i \times Investment\ opportunity_{i,t-1}$ are positive for the 2014 EMC decision and negative for the 2017 EMC decision. Treated distressed firms improve investment efficiency after the 2014 EMC decision and reduce efficiency after the 2017 EMC decision.

[Insert Table 2.14 and Table 2.15]

2.6.7 Alternative definition of level of investment

I also follow Richardson (2006) to calculate total investment as Capex + Acquisition + R&D – Sale of PPENT. Specifically, Acquisition and Sale of PPENT do not significantly change for treated and distressed firms around the decisions. Investment expenditure on new projects equals total investment - amortization and depreciation. Both total investment and investment expenditure on new projects do not significantly change in affected distressed firms around the rulings.

2.7 Summary and Implications of the Evidence

The influential 2014 and 2017 EMC rulings create a unique natural experiment for analyzing the causal effects of restructuring methods of public debt on investment policies. I test previously ambiguous theoretical predictions about this relation. After a negative shock to firms' ability to use coercive bond exchange offers in out-of-court restructurings, affected firms reduce investment, but increase volatilities and investment efficiency, compared to unaffected firms. Stock returns of affected distressed firms respond negatively to the negative shock to coercive bond exchange offers, while bond returns of affected distressed firms respond positively. The results of the 2017 EMC ruling, which reversed the 2014 ruling, support similar implications. I conclude that out-of-court restructuring of public debt through coercive bond exchange offers changes wealth allocation between shareholders and bondholders in distressed firms. However, it does not solve shareholder-bondholder agency conflicts near insolvency. In fact, it might lead to investment inefficiency.

My findings have implications for existing theoretical research in restructurings of public debt in the US. Favara, Morellec, Schroth, and Valta (2017) synthesize debt-overhang (Myers, 1977) and risk-shifting (Jensen and Meckling, 1976) and predict that weak debt enforcement increases investment and reduces risk in distressed firms. The model does not distinguish among private debt, public debt, in-court restructuring, and out-of-court restructuring. However, if I consider coercive bond exchange offers broadly as a form of weak debt enforcement, then my paper is consistent with their predictions.

Nonetheless, restructuring methods differ in more ways than just strong or weak debt enforcement. Different restructuring methods of different debt instruments could have different effects on investment. Gertner and Scharfstein (1991) consider these important differences in their model, on the basis of debt-overhang and risk-shifting theories. They take into account the fact that out-of-court restructurings of public debt under the TIA can only be accomplished through coercive bond exchange offers instead of direct renegotiation. They argue that coercive debt exchange offers can increase the incentive and ability of distressed firms to invest, but do not necessarily increase investment efficiency. My findings provide support for these predictions by showing that out-of-court restructurings of public debt increase investment but reduce investment efficiency. Bernardo and Talley (1996) explore a stronger form of agency problem in out-of-court restructurings of public debt. They demonstrate that shareholders will choose stochastically dominated projects in order to distort terms and success rates of debt exchange offers. The fact that investment efficiency increases after the negative shock to coercive bond exchange offers provides empirical support for this argument.

Similar to Gertner and Scharfstein (1991) and Bernardo and Talley (1996), my paper has practical implications for prudent legal reform. The TIA forbids votes on core terms in out-of-court restructurings of public debt, forcing debtors to use coercive bond exchange offers instead of direct renegotiations. My findings imply that this gives rise to investment inefficiency and provide empirical support for proposals that call for a repeal of section 316(b) of the TIA, thus allowing for voting in out-of-court restructurings (e.g., Gertner and Scharfstein, 1991; Bernardo and Talley, 1996; Roe, 1987, 2016; Bratton and Levitin, 2017).

3.0 Chapter 3 Capital Structure and Takeover Threats from Secured Creditors

3.1 Introduction

The effects of takeover threats through the stock market on firm performance and policies have been extensively studied (e.g., Garvey and Hanka, 1999; Giroud and Mueller, 2010; Karpoff and Wittry, 2018). Because takeovers represent threats to management entrenchment, managers have incentives to use ex ante defensive measures to lower the probability of takeovers. As documented by previous studies, one of the defensive measures employed is the use of debt, which deters takeovers by concentrating managers' percentage voting control (Stulz, 1988). According to Novaes and Zingales (1995) and Zwiebel (1996)'s theoretical predictions, managers choose their optimal capital structure to maximize entrenchment. Managers' defensive responses must walk a tightrope between the risks of bankruptcy on the one hand and the threats of hostile takeovers through the equity market on the other hand, either of which could mean loss of control. Empirical evidence supports the idea that firms use leverage to defend against equity-based hostile takeovers (Denis and Denis, 1993; Berger, Ofek, and Yermack, 1997; Garvey and Hanka, 1999).

In this study, I analyze the capital structure impact of a different type of threat to corporate control that comes from secured creditors during episodes of financial distress. Recent studies document that such threats have become more common in recent years as activist investors have taken on a greater role in the distressed debt market.[10] Using so-called loan-to-own strategies,

[10] Li and Wang (2016) find that 30% - 60% of debtor-in-possession financing cases are loan-to-own during 2005-2013. Jiang, Li, and Wang (2012) show that hedge funds adopted loan-to-own strategies in 27.7% of bankruptcy cases from 1996 to 2007. In Table 3.2 of this paper, I find that 11% of the bankruptcy cases might involve loan-to-own investment by secured creditors.

activist investors purchase discounted debt or directly lend to distressed firms, then use their voting power to push the debtor to sell assets through bankruptcy sales under Section 363 of the Bankruptcy Code. An important feature of Section 363(k) is that it allows secured creditors to bid the face value of their debt claim instead of cash, regardless of the value of the collateral at the time of the sale.[11] This gives secured creditors a large advantage over cash bidders in 363 auctions and chill other cash bidders. Congress adopted Section 363(k) as a mean for a secured creditor to protect its interests by preventing a bankruptcy sale of its collateral at an inadequate price. However, "*credit bidding has evolved into a formidable offensive weapon available to private equity, hedge funds and other investors in distressed debt who frequently are able to acquire secured debt from existing creditors at a discount and then credit bid the full amount of that debt to acquire the collateral*" (Mankovetskiy, 2011).[12] Credit bidding is a useful tool in distressed credit investment that there are constant legal battles about it (e.g., In Re: Submicron Systems Corporation, 2006; In Re Pacific Lumber Co. , 2009; In re Philadelphia Newspapers, LLC, 2010; In re RadLAX Gateway Hotel, LLC, 2012; In re Fisker Automotive Holdings, Inc., 2014; In re RML Development, Inc, 2014; In re Free Lance-Star Publishing Co., 2014; In re RadioShack Corp., 2015).

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[11] 363 (k): "At a sale under subsection (b) of this section of property that is subject to a lien that secures an allowed claim, unless the court for cause orders otherwise the holder of such claim may bid at such sale, and, if the holder of such claim purchases such property, such holder may offset such claim against the purchase price of such property."

[12] Boris Mankovetskiy, "The Nuts And Bolts Of Credit Bidding: A Primer For Traditional Lenders And Distressed Debt Investors"

For example, in the bankruptcy of Fisker Automotive Holdings, Inc., a hedge fund purchased an outstanding principal balance of $168.5 million senior secured debt at only $25 million shortly before the bankruptcy filing. In a 363 sale, the hedge fund attempted to acquire all of Fisker's assets with a $75 million credit bid. If the hedge fund is allowed to credit bid at $75 million, then there would be one of two possible results. First, other cash bidders pay at least $75 million in cash to win the auction and acquire Fisker's assets. The hedge fund, in this scenario, receives the proceeds of the auction. Second, no cash bidder bids more than $75 million. In this scenario, the hedge fund then acquires Fisker's assets without paying an extra dollar beyond the initial $25 million spent. Even if the market value of assets is higher than the face value, credit bidders can use a combination of credit bid and cash bid to win the auction.

The threat to control from such ‘credit-bidding’ differs from equity-based takeover threats in that it threatens not only incumbent managers, but also the equity position of shareholders. Consequently, I hypothesize that firms facing such threats will adjust leverage, ex ante, in order to reduce the likelihood of a takeover via a Section 363 sale. Specifically, firms will attempt to minimize the likelihood of a control threat by reducing leverage and lowering the probability of distress. Moreover, contrary to defensive increases in leverage in response to equity-based takeover threats, which result in decline in shareholder wealth (Dann and DeAngelo, 1988; Denis, 1990), I expect defensive decreases in leverage to be in shareholders’ interests because they make it less likely that the shareholder’s equity option will be extinguished in the process of financial distress.

To test these propositions, I rely on a legal challenge to the credit-bidding strategy that represents an exogenous shock to bankruptcy-related control threats from secured creditors. The case, Radlax Gateway Hotel, et al., v. Amalgamated Bank (U.S. Supreme Court 2012), challenged tactics employed by debtors that had limited the ability of secured creditors to obtain control through credit-bidding strategies. After split decisions in the Circuit Courts, the U.S. Supreme Court affirmed in its May 29, 2012 decision the right of secured creditors to credit bid up to the face value of their claim. I treat this decision, therefore, as a positive shock to the likelihood of a control transfer to secured creditors and creates a difference-in-differences (DID) setting to test the causal relation between takeover threats from secured creditors and debt financing policies.

My empirical analysis begins by confirming that the Supreme Court decision has a material impact on the use of credit bidding, the frequency of 363 sales, and the wealth of stockholders of distressed firms. Specifically, the average frequency of 363 sales among Chapter 11 cases increases from 18% to 29% after the 2012 decision, and the percentage of Chapter 11 cases that include credit bids increases from 8% to 12%. The increases in 363 sales and credit bidding in bankruptcy imply that secured creditors more frequently acquire assets of distressed targets through bankruptcy sales after the 2012 decision. Distressed firms with high secured debt-to-total debt ratios (hereinafter "secured debt ratio") exhibit negative stock price reactions to the May 29, 2012 Supreme Court decision. The court decision significantly increases takeover threats from secured creditors and, consequently, increases the likelihood that the shareholders' equity option would be either extinguished or reduced in value.

Having established this, I then proceed to test whether distressed firms make ex ante adjustments to their financial structure. Firms can deter activist secured creditors by deleveraging because it prevents credit-bidding or lowers profits of credit-bidding. Consistent with this view, I find that leverage decrease more in distressed firms than in non-distressed firms following the 2012 decision. The marginal effect is around 13.4% of the average leverage. The leverage is reduced through net debt issuance reduction instead of net equity issuance increase. The deleveraging is particularly prominent in firms with high secured debt ratios, which are more exposed to the shock. The leverage also decreases less in firms with high probabilities of hostile takeover through the equity market because self-entrenching managers, who use debt to deter equity-based takeovers, are relatively reluctant to reduce leverage. However, these firms instead reduce secured debt ratios in response to the shock.

In further results, I find that deleveraging in response to the 2012 decision is greater in firms with higher CEO pay-performance sensitivity. This supports the view that CEOs are more likely to take actions to reduce the likelihood of a takeover threat from secured creditors when their interests are aligned with those of shareholders. Finally, consistent with the 2012 legal ruling specifically benefitting secured creditors, I find that offering yields of secured debt fall relatively to those of unsecured debt.

My paper extends the recent literature on loan-to-own investment strategy by examining takeover threats from loan-to-own investors. Gilson, Hotchkiss, and Osborn (2016) study M&As in bankruptcy and find that while tighter credit markets and secured debt are positively related to sales in bankruptcy, M&As in bankruptcy is not inefficient liquidation. My findings complement the work of Li and Wang (2016), who compare loan-to-loan lenders and loan-to-own lenders in debtor-in-possession financing under Chapter 11 and find that loan-to-own lenders target smaller firms and improve distressed firms' corporate governance. Harner (2011) compares the use of debt-based and equity-based takeovers using case studies. These papers study debt-based acquisitions that have already taken place, while I study the possibility of being targeted and the defensive leverage adjustments.

My paper also supplements the literature on takeover threats through the equity market and capital structure. Theoretical research predicts that managers choose a capital structure to maximize their ability to empire-build (reduce leverage) subject to ensuring sufficient efficiency to prevent a takeover (increase leverage) (e.g., Stulz, 1988; Zwiebel, 1996; Novaes, 2002). Consistent with these predictions, empirical papers find that takeover threats induce managers to take on debt they would otherwise avoid (e.g., Denis and Denis, 1993; Garvey and Hanka, 1999). Francis, Hasan, John, and Waisman (2010) show that when takeover threats through the stock market increase, at-issue yield spreads are higher because managers will maximize shareholder value, to the detriment of bondholders. To my knowledge, this paper is the first one to examine probabilities of hostile takeovers by secured creditors, and to examine the tradeoff between these two competing types of takeover threats in capital structure decisions.

3.2 Background and Hypotheses Development

3.2.1 Loan-to-own strategy in firms with high default probabilities

Loan-to-own investors extend credit[13] to, or purchase the debt of, a financially distressed target and acquire the target through a debt-for-equity exchange or credit bid in bankruptcy sales. In the first channel, they attempt to identify and purchase the distressed company's fulcrum security (i.e., the claim that is not expected to be paid in full). Then, they renegotiate with debtors out-of-court or in-court to control the target by converting debt ownership into majority equity ownership.

In this paper, the natural experiment is only related to secured creditors' ability to acquire the target through the second channel, i.e. credit bid in bankruptcy sales. Most distressed firms first try to restructure their debt out-of-court. If activist secured creditors do not attain their goal in the renegotiation, they can push the firm to Chapter 11 bankruptcy. Under Chapter 11, debtor-in-possession has the first chance to propose a reorganization plan for creditors to vote about how it will operate and pay its obligations in the future. A reorganization plan must be approved by all classes of creditors and confirmed by the court. If activist creditors have enough voting rights in a class (2/3 in the dollar amount and 1/2 in number), they can vote down the plan and urge debtors to sell assets through 363 sales. Section 363 of the Bankruptcy Code allows debtor-in-possession to sell assets to settle their debts with several advantages, including "speed, transfer of assets free and clear of encumbrances and interests, transfer of restricted contracts, and avoidance of exposure to claims under fraudulent transfer laws"[14].

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[13] Loan-to-own investors could offer debtor-in-possession lending with a first-priority priming lien and strict covenants, and gain control over the bankruptcy process. For example, in pre-packaged bankruptcy of American Gilsonite, DIP lenders convert their debt to 98% of the new equity of the reorganized company.
[14] Pathology of Section 363 Sales, FindLaw

To start a 363 sale, debtors should find a proposed purchaser (i.e., "stalking horse" bidder) and file a motion for a bankruptcy auction. The “stalking horse” bidder will be the initial bidder and set the minimum bid. Upon approval, debtors try to hold a competitive auction and select the highest bid. If no other bidder participates, then the "stalking horse" bidder purchases assets according to the agreement. The bankruptcy court needs to approve the sale of the debtor's assets, considering the interests of all parties. Activist secured creditors frequently employ debt-based acquisition in 363 sales through credit-bidding. Credit-bidding allows a secured creditor to bid for and purchase its collateral using the outstanding debt as payment. It gives secured creditors an advantage over cash bidders because many activist secured creditors invest distressed secured debt at a discount. Credit-bidding can further facilitate creditor’s control by chilling a competitive bidding process when the creditor’s collateral value is less than the creditor’s remaining loan balance.

Although credit-bidding is a powerful and profitable tool, it is not absolute. Debtors sometimes manage to prevent secured creditors from credit-bidding. Even if at least one class of creditors votes against a reorganization plan, the debtor can still persuade the judge to cram it down under Section 1129(b) of the Bankruptcy Code [15]. The court can cram down a reorganization plan over

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[15] Chapter 11, Section 1129, Confirmation of plan:
“With respect to a class of secured claims, the plan provides—
(i)
(I)
that the holders of such claims retain the liens securing such claims, whether the property subject to such liens is retained by the debtor or transferred to another entity, to the extent of the allowed amount of such claims; and
(II)
that each holder of a claim of such class receive on account of such claim deferred cash payments totaling at least the allowed amount of such claim, of a value, as of the effective date of the plan, of at least the value of such holder’s interest in the estate’s interest in such property;
(ii)
for the sale, subject to section 363(k) of this title, of any property that is subject to the liens securing such claims, free and clear of such liens, with such liens to attach to the proceeds of such sale, and the treatment of such liens on proceeds under clause (i) or (iii) of this subparagraph; or
(iii)

dissenting secured creditors if it meets one of three requirements. (i) Secured creditors may retain its lien on the property and receive deferred cash payments. (ii) The collateral is sold free and clear of the secured creditor's lien through a 363 sale, and creditors can credit bid at the sale — and the creditor receives a lien on the sale proceeds. (iii) The holders realize the "indubitable equivalent" of their secured claims.

According to clause (i) and (ii), secured creditors must be able to either keep the collateral or credit bid when selling the collateral in a 363 sale under a cramdown plan. However, some debtors manage to sell secured creditors' collateral under a cramdown plan, without letting dissenting secured creditors credit bid. Specifically, they build the bankruptcy sale into a Chapter 11 plan and then try to substitute credit bidding with an "indubitable equivalent" right. The right is often not entirely equivalent to credit bid. Still, their reorganization plan can be confirmed over the objection of secured creditors because it meets clause (iii). There are different opinions about the legality of this strategy. Third Circuit and Fifth Circuit upheld this strategy in 2009 and 2010[16]. Seventh Circuit rejected this strategy and insisted that secured creditor's right to credit bid could not be expropriated by a judicial estimation of indubitable equivalence[17].

On May 29, 2012, the U.S. Supreme Court resolved the split in Radlax Gateway Hotel, et al., v. Amalgamated Bank by affirming Seventh Circuit's opinion. The Supreme Court required a cramdown plan to meet both clause (ii) and (iii). That means, when selling a secured creditor's collateral in bankruptcy sales, the debtor must allow the creditors to credit bid. The ruling also confirmed that secured creditors could credit bid up to the face amount of their secured claims,

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for the realization by such holders of the indubitable equivalent of such claims."

[16] In re The Pacific Lumber Co., (5th Cir. 2009); In re Phila. Newspapers LLC, (3d. Cir. 2010)

[17] In re River Road Hotel Partners LLC, (7th Cir. 2011)

even though they purchased the claims at a deep discount. I use this event as an exogenous positive shock to the use of credit bidding and, therefore, takeover threats from secured creditors.

Although debt-based acquisition is a type of debt investment, its effect on the debtor is not completely the same as that of tradition debt investment. Debt-based acquisition is different from traditional debt investment in many ways. First, loan-to-own investors are usually PE, VC, or vulture funds, who are experienced in activist distressed debt investment. They profit from taking control and changing the firms' operation or performance (e.g., Kmart and ESL Investment[18]). Loan-to-own investors may employ debt-based takeovers to enhance their existing portfolio by combining companies with similar platforms or quieting the competition. Second, traditional lenders attempt to choose claims that are likely to be fully repaid, while loan-to-own investors attempt to choose the type and amount of debt claims that just allow them to control the restructuring process and the debtor. Sometimes they try to acquire the fulcrum security (i.e., the claim that is not expected to be paid in full), because it maximizes their leverage over approval of the debtor's reorganization plan and allows them end up owning the debtor. Third, loan-to-own investors infuse capital to a target with limited alternatives, with tricky details in loan contracts. For example, the debt contract may impose stringent covenants, provide the lenders with control or veto rights, add credit bid as a precondition, or otherwise set up the company for eventual failure (Harner, 2011).

[18] ESL Investments used loan-to-own to control 53% of Kmart for an investment of less than $1 billion in 2003. The CEO of ESL Investments became the chairman of Kmart and improved the company's balance sheet by reducing inventory, cutting costs, and closing underperforming stores. In 2004, he merged Kmart and Sears.

3.2.2 Hypotheses development

As discussed in Section 3.2.1, Radlax Gateway Hotel, et al., v. Amalgamated Bank facilitates loan-to-own investors to acquire assets through credit bidding. The event reduces the risk of an unsuccessful loan-to-own investment, and consequently more investors will start from acquiring secured loans and control a distressed target.

H1: After takeover threats from secured creditors increase, the frequency of bankruptcy sales and credit bidding increase.

Previous literature shows that takeover threats through the stock market have a positive effect on stock returns because they have a disciplinary effect on managers (Grossman and Hart, 1980; Scharfstein, 1988; Low, 2009; Giroud and Mueller, 2010). Loan-to-own investors impose similar takeover threats that provide additional incentives for the board to discipline or replace incumbent managers. Li and Wang (2016) find that Chapter 11 firms with loan-to-own debtor-in-possession lenders improve governance at the emergence (i.e., CEO turnover, board turnover, and board independence). Nevertheless, loan-to-own investors aggressively acquire assets, while target shareholders suffer from low recovery rates or loss of control. After a positive shock to takeover threats from secured creditors, shareholder value will decrease. Because the natural experiment only directly facilitates secured creditors' takeover through bankruptcy sales, firms with a large amount of outstanding secured debt are more susceptible to the shock. Meanwhile, unsecured creditors are not directly affected by the event. Thus, costs of secured debt fall relative to costs of unsecured creditors. The value effects of shareholder, secured creditor, and unsecured creditor are ideally tested using short-window event studies. Due to the data limitation and low trading frequency of debts, I investigate the change of at-issue yields of secured and unsecured debts.

H2a: After takeover threats from secured creditors increase, stock returns in firms with high default probabilities decrease, especially for firms with high secured debt-to-total debt ratios.

H2b: After takeover threats from secured creditors increase, costs of secured debt decrease relative to costs of unsecured debt.

Stulz (1988) and Israel (1991) predict that the probability of being targeted in the equity market decreases with leverage because debt is a useful tool for takeover defenses. Managers use debt to concentrate their voting control and make targets less valuable to acquirers in the equity market. Empirical research shows that managers use leverage (Denis and Denis, 1993; Garvey and Hanka, 1999), payout (Denis, 1990), and corporate asset and ownership restructurings (Dann and DeAngelo, 1988) to deter equity-based takeovers. A positive shock to takeover threats from secured creditors reduces leverage for two reasons. First, to prevent activist investors from gaining control over targets in a breach of the covenant or default, managers reduce leverage to avoid financial distress. Second, firms with low leverage have high current debt values. A small difference between face value and current price of debt can reduce profits of credit-bidding.

H3a: After takeover threats from secured creditors increase, firms with high default probabilities reduce leverage, especially for those with high secured debt-to-total debt ratios.

The debt-based and equity-based takeovers could substitute each other as a method to acquire a distressed target. If equity-based takeover is easy, then acquirers are less likely to replace equity-based takeover with debt-based takeover even after the 2012 decision. Firms do not need to deleverage to deter the loan-to-own takeover in response to the shock. If equity-based takeover is difficult, then acquirers are more likely to switch to debt-based takeover after the 2012 decision. Firms have to deleverage to deter the loan-to-own takeover after the 2012 decision.

H3b: After takeover threats from secured creditors increase, firms with high default probabilities reduce leverage, especially for those with less takeover threats from the equity market.

3.3 Data and Methodology

3.3.1 Empirical methodology

I follow the difference-in-differences approach to estimate the following model:

$$y_{i,t} = \gamma Treat_i * Aft_t + \delta X_{i,t-1} + \alpha_t + \beta_i + \varepsilon_{i,t} \qquad (1)$$

where i indexes firms and t indexes year-quarters. $Treat_i$ takes the value of one if a firm's default probability in January 2010 is in the top 30 percentile. Aft_t takes the value of one after 2012Q2. Dependent variable $y_{i,t}$ denotes $Leverage_{i,t}$ or debt structure variables. $X_{i,t-1}$ is a vector of firm-level control variables. α_t is time year-quarter fixed effects and β_i is firm fixed effects. $Treat_i$ and Aft_t are dropped because of collinearity after controlling for the fixed effects. I adjust standard errors by clustering the observations at the firm level.

3.3.2 Data and summary statistics

I begin with quarterly corporate financial data of all U.S. firms in 2010 - 2014 from Compustat, excluding financial services firms (SIC 60-69). I rely on LoPucki's Bankruptcy Research Database for Chapter 11 filing data. Debt issuance and debt structure data come from Capital IQ. I use the firm-level takeover susceptibility index from Cain, McKeon, and Solomon (2017) to measure takeover threats through the equity market. The default probability is calculated using the Merton distance to default model (SAS code from Bharath and Shumway (2008)). I obtain CEO incentive data from Execucomp, Core and Guay (2002) and Coles, Daniel, and Naveen (2006). The final sample contains 2,345 unique firms. I also present evidence on stock and bond price reaction to the 2012 decision. I extract daily stock return and bond return data from CRSP and TRACE.

Table 3.1 reports summary statistics of quarterly financial data in full sample, treated, and control groups. As discussed in Section 3.3.1, treated firms are those with top 30 percentile default probability in January 2010. The rest of the companies serve as control firms. The main dependent variable is $Leverage_{i,t}$ and is defined as (dlttq+dlcq)/atq. I include several firm-specific control variables. $ROA_{i,t-1}$ is net income scaled by total assets ($niq_{i,t-1}/atq_{i,t-1}$). *Stock return*$_{i,t-1}$ is calculated as ($prccq_{i,t-1}$/ $prccq_{i,t-2}$)-1. $Size_{i,t-1}$ is measured as natural logarithm of $atq_{i,t-1}$. $PPENT_{i,t-1}$ is ppentq/atq in quarter t-1. *Market-to-book*$_{i,t-1}$ is (prccq×cshoq)/ceqq in quarter t-1. *Net debt issuance*$_{i,t}$ is (quarterly change of dltisy-quartely change of dltry)/atq. *Net equity issuance*$_{i,t}$ is (quarterly change of sstky-quartely change of prstkcy)/atq. Cain, McKeon, and Solomon (2017)'s takeover susceptibility index is constructed using takeover laws related to traditional hostile takeovers through the stock market (e.g., 1st Generation Statutes, Business Combination, Fair Price, Control Share Acquisition, etc.), macroeconomic factor, and firm age. I winsorize all continuous variables at the 1st and 99th percentiles.

As expected, firm characteristics of treated and control firms are different. Treated firms have higher leverage and lower ROA than control firms. *(Secured debt/Total debt)*$_{i,t}$ is also significantly higher in the treated group than in control group. Treated firms also tend to have higher PPENT and net equity issuance. The differences between treated and control firms might drive the changes in leverage and debt structure around May 29, 2012. In Section 3.5.2, I conduct a Propensity Score Matching-DID analysis to address for this concern.

[Insert Table 3.1]

3.4 Empirical Results

3.4.1 The frequency of 363 sales and credit-bidding in bankruptcy

To show the takeover threats from secured creditors is non-trivial after May 2012, I summarize the frequency of credit bidding and 363 sales in Chapter 11 bankruptcy in Table 2. The use of 363 sales under Chapter 11 is collected from LoPucki's Bankruptcy Research Database. I hand-collect information about credit-bid for each 363 sale. Details about credit-bidding are reported in the Appendix. Li and Wang (2016) define secured bank lenders as loan-to-loan lenders and activist investors as loan-to-own lenders. Although it is difficult to observe the motivation of creditors, the classification is reasonable based on fundamental differences in investment strategy of different institutional investors. In Appendix, only one of the credit bidders is a secured bank lender, while other credit bidders are hedge funds or private equity funds, which specialize in acquisition or distress debt investment (e.g., The Gores Group, Oaktree Capital Management).

After the event in 2012, 363 sales were more frequently used under Chapter 11. Before 2012, 14% - 21% of the Chapter 11 cases end up with 363 sales. The frequency increases to 24% - 35% after 2012. Credit-bidding becomes more common. The frequency of Chapter 11 cases that involve credit-bidding increase from 5% - 11% to 8% - 16% around 2012. There might be a concern that the frequency of credit-bidding is low (0.17% - 0.62% among firms with top 30% default probabilities), and therefore, management would not look ahead to this remote possibility to adjust leverage. However, M&A is a rare event by nature. There are 63-84 public deals through equity-based takeover from 2010 to 2014. There are around 4,000 non-financial public firms during the sample period. Thus, the probability of being acquired through equity-based takeover is 1.5% - 2.1%. Previous literature documents that managers respond to the change in takeover threats from the equity market (e.g., Garvey and Hanka, 1999; Cheng, Nagar, and Rajan, 2005; Low, 2009). Thus, debt-based takeovers by secured creditors through credit-bidding in bankruptcy pose a real threat to managers in firms near insolvency, especially after Radlax Gateway Hotel, et al., v. Amalgamated Bank.

[Insert Table 3.2]

3.4.2 The value of shareholder, secured creditor, and unsecured creditor

3.4.2.1 Shareholder value

As discussed in Section 3.2.1, Radlax Gateway Hotel, et al., v. Amalgamated Bank on May 29th, 2012 directly facilitates debt-based takeovers by secured creditors. In this section, I conduct an event study analysis to evaluate the welfare impact and show that this event is influential. Expected stock returns are estimated using the Fama-French three-factor model within an estimation window [-150, -50]. I calculate stock CARs over [-5, 5], [-3, 3], [-1, 1], and [0] event windows. Distressed firms with a large amount of outstanding secured debt are the most susceptible to the event, and thus, I report subsample tests of CARs. I define subsamples according to two measures, default probabilities in January 2010 and secured debt ratios in 2010Q1. Two-sample t-tests are used to compare stock CARs between different subsamples.

Table 3.3 Panel A shows that stock CARs of firms with high default probabilities are significantly negative in [-5, 5]. After takeover threats from secured creditors increase, stock CARs are significantly lower in firms with high default probabilities than in firms with low default probabilities. The difference is only significant in firms with above-median secured debt ratios. The event does not influence stock returns when firms have below-median secured debt ratios. Stock CARs of [-3, 3] and [-1, 1] in Panel B and C are similar to those in Panel A. Overall, results in Table 3.3 are consistent with H2a that stock returns in firms with high default probabilities and secured debt-to-total debt ratios decrease after takeover threats from secured creditors increase. Although it is always difficult to predict how the Court will rule from the oral argument, professionals can sometimes do that from the general tone. The oral argument was held on April 23, 2012, and some professionals think that creditors might win. However, I do not find similar event study results around April 23, 2012.

[Insert Table 3.3]

3.4.2.2 At-issue debt yields

As discussed in Section 3.2, the event only benefits secured creditors by facilitating secured-debt-based acquisitions. Junior claimants (equity holders and unsecured creditors) are unaffected or experience lower recovery rates. Table 3.3 presents evidence about the negative effect on shareholder value. To further test this hypothesis, I investigate the change of costs of secured and unsecured debts around the 2012 decision. Although it is ideal to use the short-window event study of secured and unsecured debt returns, I compare the relative changes of at-issue secured and unsecured debt yields because of the limited data and low trading frequency of public debts. I collect new issues of secured and unsecured debt in 2010 – 2014 from Capital IQ. Table 3.4 shows the change in at-issue secured debt yields relative to unsecured debt yields around the event. *Secured debt*$_{i,j,t}$ equals one if debt *j* issued by firm *i* is secured, and zero otherwise. Column 1 controls for year×quarter fixed effects. *Secured debt*$_{i,j,t}$ is significantly positive and *Secured debt*$_{i,j,t}$ × *Aft*$_t$ is negative. The negative coefficient of *Secured debt*$_{i,j,t}$ × *Aft*$_t$ implies that costs of secured debt decrease relative to costs of unsecured debt after takeover threats from secured creditors increase. The positive coefficient of *Secured debt*$_{i,j,t}$ suggests that costs of secured debt are higher than those of unsecured debt, which is counter-intuitive. It illustrates the selection problem of secured debt: creditors will demand collateral from risky borrowers (e.g., Benmelech and Bergman, 2009; Benmelech, Kumar, and Rajan, 2020). To address for this concern, I follow Benmelech, Kumar, and Rajan (2020) to include firms fixed effects, firm×year fixed effects, firm×year×quarter fixed effects in Column 2 to 4. After including those fixed effects, coefficients of *Secured debt*$_{i,j,t}$ become negative, which is consistent with the intuition that debts with collaterals have lower costs. Coefficients of *Secured debt*$_{i,j,t}$ × *Aft*$_t$ remain negative, costs of secured debt decrease relative to costs of unsecured debt after the event.

[Insert Table 3.4]

3.4.3 Main results

3.4.3.1 The change in leverage

A core assumption of DID is that there is no pre-existing differential trend between treated and control firms. I validate this parallel trend in Figure 3.1. Figure 3.1 presents coefficients of interactions between year-quarter dummy variables and *Treat*$_i$ and 95% confidence intervals of coefficients in the regression of *Leverage*$_{i,t}$. The event date 0 is 2012Q3. Before 2012Q3 (t=0), the average differences in *Leverage*$_{i,t}$ between treated and control firms are not statistically different from that in 2011Q1 (t = -6). The trend in outcome for treated and control groups prior to the event are stable. After 2012Q4 (t=1), the differences in $Leverage_{i,t}$ are always smaller than those in 2011Q1. The sum of all significant coefficients of interactions between year-quarter dummy variables and $Treat_{i,t}$ from 2012Q4 to 2013Q4 is -0.12. Distressed firms accumulatively reduce leverage more than control firms by 0.12 after the positive shock to takeover threats from secured creditors. The magnitude equals 50.4% of the average leverage.

[Insert Figure 3.1]

Table 3.5 presents the results of the difference-in-differences regression Equation (1). I regress $Leverage_{i,t}$ on $Treat_i \times Aft_t$ and control variables. Column 1 of Table 3.5 is the baseline regression. The coefficient on the interaction between $Treat_i$ and Aft_t is negative and statistically significant. After takeover threats from secured creditors increase, firms with high default probabilities reduce leverage relative to other firms. The marginal effect in the regression of leverage is -0.032, which is 13.4% of the average leverage. Garvey and Hanka (1999) observe four-year cumulative abnormal leverage reductions of about 30 percent following protection by antitakeover laws (equity-based takeover threat decreases). Thus, this magnitude is in a reasonable range.

The shock only directly increases takeover threats from secured creditors through bankruptcy sales and does not facilitate takeovers by junior creditors through debt-to-equity conversion. Firms with high default probabilities and large amounts of outstanding secured debt are more vulnerable to the event. $Secure_i$ equals one if firm i has above median secured debt-to-total debt ratios in 2010Q1, and zero otherwise. In Column 2, the coefficient of $Treat_i \times Aft_t \times Secure_i$ is significantly negative, implying that firms with outstanding secured debts are more concerned about takeover threats from secured creditors and reduce leverage to deter those potential takeovers. The magnitude of the effect among firms with high secured debt-to-total debt ratios is -0.017-0.033= -0.05, which is 21% of the average leverage level.

In Column 3, I further show the countervailing effects of takeover threats through the equity market and those through the credit market. $Takeover_i$ is a dummy variable, which equals one if firm i has above median takeover susceptibility index in 2009. The coefficient of $Treat_i \times Aft_t \times Takeover_i$ is significantly positive, suggesting that firms with high takeover threats from the equity market deleverage less. The magnitude of the effect on these firms is -0.043+0.020= -0.023 (9.7% of the average leverage level), which is smaller than the magnitude of in the baseline regression. This could be explained by two mutual inclusive reasons. First, raiders choose either equity-based or debt-based takeovers to acquire a distressed target. If equity-based takeover is easy (i.e., high probability of hostile takeovers), then they are less likely to switch to debt-based takeover after 2012. Firms do not need to deleverage to deter potential debt-based takeovers. Second, managers' career concerns discourage them to deleverage in firms with high equity-based takeover threats. Managers are reluctant to reduce leverage in response to the 2012 decision when they are simultaneously faced with takeover threats through the equity market. If they reduce leverage, firms are likely to be targeted in the equity market as well. On one hand, managers are concerned about both types of takeover threats. On the other hand, shareholders benefit from takeover threats through the equity market and only worry about takeovers from creditors (e.g., Karpoff and Malatesta, 1989; Dann and DeAngelo, 1988). Therefore, there exists a conflict of interest between managers and shareholders in capital structure decision when takeover threats from secured creditors increase. In Section 3.4.4, I exhibit that high CEO pay-performance incentives can align the interests of CEOs with shareholders, and further encourage CEOs to reduce the leverage.

[Insert Table 3.5]

3.4.3.2 The change in secured debt ratio

Alternatively, managers can deter takeovers from secured creditors by reducing the amount outstanding secured debt. If loan-to-own investors cannot acquire enough secured debts, they cannot easily control a significant part of the assets even in bankruptcy. In Table 3.6, I estimate the effects of takeover threats from secured creditors on *(Secured debt/Total debt)*$_{i,t}$ and *(Unsecured debt/Total debt)*$_{i,t}$. Dependent variables in Columns 1, 3, and 5 are *(Secured debt/Total debt)*$_{i,t}$ and *(Unsecured debt/Total debt)*$_{i,t}$ in Columns 2, 4, and 6. The quarterly data of capital structure is obtained from Capital IQ. $Treat_i$, Aft_t, $Secure_i$, and $Takeover_i$ are the same as in Table 3.6. $Treat_i \times Aft_t$ is insignificant in Column 1 & 2. Although distressed firms can deter takeover threats from secured creditors by reducing secured debt amount, secured debt-to-total debt ratio and unsecured debt-to-total debt ratio do not significantly change. While distressed firms generally deleverage after the 2012 decision, they do not always reduce secured debt ratios..

The coefficient of $Treat_i \times Aft_t \times Takeover_i$ is significantly negative in Column 3 and positive in Column 4. In Table 3.5, managers deleverage less when equity-based takeover threats are high. Instead, they reduce secured debt ratios so that secured creditors cannot acquire a large amount of assets even in bankruptcy. Consistently, unsecured debt ratio increases in those companies. This implies that reducing leverage and secured debt ratio are two substituted ways to deter takeovers from secured creditors. In Columns 5 and 6, coefficients of $Treat_i \times Aft_t \times Secure_i$ are insignificantly different from zero. Affected firms with high secured debt ratios does not significantly change secured and unsecured debt ratios, compared to affected firms with low secured debt ratios.

[Insert Table 3.6]

Although it is difficult to reduce the outstanding amount of secured debts before maturity dates, it is relatively easy to avoid issuing new secured debt immediately after the shock. Table 3.7 shows the result of Probit regression of issuing new secured debt. The dependent variable *Secure debt*$_{i,j,t}$ is a dummy variable, which equals one if debt j issued by firm i is secured. I include firm-level and debt-level characteristics in the model. I also control for industry (Fama-French 17 industries) and year-quarter fixed effects. The negative coefficient of $Treat_i \times Aft_t$ suggests that firms with high default probabilities are less likely to issue secured debt after the 2012 decision.

[Insert Table 3.7]

3.4.3.3 Composition of the change in leverage

I further study the composition of the change in leverage. Do they increase equity issuance or reduce debt issuance? Table 3.8 provides estimates of net debt issuance around the event. Net debt issuance is calculated as (Long-term debt issuance - Long-term debt reduction)/Total assets. In the baseline regression, the coefficient of $Treat_i \times Aft_t$ is insignificantly different from zero, implying that firms with high default probabilities do not reduce net debt issuance after takeover threats from secured creditors increase. In Column 2, the coefficient of $Treat_i \times Aft_t \times Secure_i$ is insignificantly negative. Affected firms with high secured debt ratios do not reduce net debt issuance. In untabulated results, I conduct subsample tests according to secured debt ratio in 2010Q1. The coefficient of $Treat_i \times Aft_t$ is -0.004 (P-value=0.059) in the regression of firms with above median secured debt ratios in 2010Q1. The coefficient is -0.000 (P-value=0.979) for firms with below median secured debt ratios in 2010Q1. The results weakly support that affected firms with high secured debt ratios deleverage by reducing net debt issuance. The coefficient of $Treat_i \times Aft_t \times Takeover_i$ is significantly positive in Column 3. Similar to Table 3.5, firms deleverage by reducing net debt issuance only when they have low hostile takeover threats through the equity market.

[Insert Table 3.8]

In Table 3.9, I examine whether firms reduce leverage by increasing net equity issuance. The dependent variable net equity issuance is calculated as (Sale of Common and Preferred Stock - Purchase of Common and Preferred Stock)/Total assets. $Treat_i \times Aft_t$, $Treat_i \times Aft_t \times Secure_i$, $Treat_i \times Aft_t \times Takeover_i$ are insignificant in all the regression. Treated firms do not deleverage by increasing net equity issuance as a source of capital. They simply reduce net debt issuance and capital raised from external capital market.

[Insert Table 3.9]

3.4.4 Additional results: CEO incentives and leverage

A fundamental difference between debt-based takeover threats and equity-based takeover threats is the incentives of managers and shareholders. When equity-based takeover threats increase, managers increase leverage to concentrate voting powers or commit to an increase in firm value to secure their jobs (e.g., Stulz, 1988; Novaes and Zingales, 1995; Zwiebel, 1996). Managers and shareholders have opposite strategies of capital structure when takeover threats through the equity market increase. Shareholder value declines after managers deter hostile takeover attempts (Dann and DeAngelo, 1988). Thus, shareholders do not want to increase leverage to deter equity-based takeovers. Safieddine and Titman (1999) document a high management turnover rate in lever-up targets following failed takeover attempts.

When loan-to-own takeover threats increase, both managers and shareholders have incentives to reduce leverage to defend against debt-based acquirers. As discussed in H3a, managers with career concerns reduce leverage to prevent debt-based acquirers from controlling the distressed debtor. Shareholders have the same goal because they have low recovery rates after secured creditors successfully credit-bid. Nevertheless, managers are relatively more reluctant to reduce leverage, compared to shareholders. If managers reduce too much debt, they will lose barriers against equity-based hostile takeovers, in which case they might still lose their jobs. A high CEO pay-performance sensitivity can align the interests of CEOs with shareholders, encouraging CEOs to deleverage more.

The results are presented in Table 3.10. $Delta_{i,t-1}$ is CEO pay-performance sensitivity, i.e., dollar change in CEO wealth associated with a 1% change in the firm's stock price (in $000s) in quarter t-1. CEO delta is obtained from Core and Guay (2002) and Coles, Daniel, and Naveen (2006). The coefficient of $Treat_i \times Aft_t \times Delta_{i,t-1}$ is significantly negative and the coefficient of $Treat_i \times Aft_t$ is insignificant. After the positive shock to takeover threats from secured creditors, distressed firms do not significantly deleverage. If the CEO pay-performance sensitivity is high, then CEOs deleverage in the interests of shareholders although deleveraging increases the probabilities of equity-based takeovers.

[Insert Table 3.10]

3.5 Robustness Analyses

3.5.1 Financial crisis and foreign firms

In this section, I investigate whether my primary findings are robust to confounding or alternative explanations. Because my sample period is from 2010 to 2014, an alternative explanation is treated firms (firms with high default probabilities) have high leverage during the financial crisis. Thus, leverage in these firms decreases more after the crisis. In Table 3.11, I investigate this alternative explanation using Compustat foreign companies as the sample. Foreign firms are affected by the financial crisis but are not directly influenced by the US bankruptcy system. If the financial crisis leads to the change in leverage, then foreign firms with high default probabilities will reduce leverage after 2012Q2 as well. $Treat_i \times Aft_t$ and $Treat_i \times Aft_t \times Secure_i$ are insignificant in regressions of $Leverage_{i,t}$. After the 2012 decision, foreign firms with high default probabilities and high secured debt-to-total debt ratios do not reduce leverage. The main result is driven by the positive shock to takeover threats from secured creditors instead of the financial crisis. Figure 3.2 presents coefficients of interactions between year-quarter dummy variables and $Treat_i$ and 95% confidence intervals of coefficients in the regression of $Leverage_{i,t}$. The patterns of differences in $Leverage_{i,t}$ between treated and control foreign firms are stable before and after the event.

[Insert Table 3.11]

[Insert Figure 3.2]

3.5.2 Propensity score matching and difference-in-differences

In Table 3.1, firm characteristics between firms with high and low default probabilities are different. To make treated and control firms more comparable, I conduct a Propensity score matching – DID analysis by one-to-one matching without replacement between treated and control firms. The propensity score is estimated using the logistic regression with covariates including leverage, size, ROA, Market-to-book, and PPENT in 2012Q2. Table 3.12 tabulates summary statistics of the full sample, treated firms, and matched control firms. The differences in leverage, ROA, and debt structure between treated and control groups are smaller in Table 3.12 than in Table 3.1.

[Insert Table 3.12]

I use the matched sample to conduct the main tests of leverage and debt structure. Table 3.13 reports the change in leverage around the positive shock to takeover threats from secured creditors. $Treat_i \times Aft_t$ is significantly negative in all three regressions. $Treat_i \times Aft_t \times Secure_i$ is significantly negative, and $Treat_i \times Aft_t \times Takeover_i$ is significantly positive. The results are similar to those in Table 3.5 and confirm H3a and H3b. Table 3.14 shows the changes in Unsecured debt/Total debt and Secured debt/Total debt around the 2012 decision. $Treat_i \times Aft_t$ is insignificantly different from zero in baseline regressions. $Treat_i \times Aft_t \times Takeover_i$ is significantly negative in the regression of Secured debt/Total debt and positive in the regression of Unsecured debt/Total debt. Similar to the results in Table 3.5, affected firms reduce secured debt ratios instead of leverages to deter debt-based takeovers when equity-based takeover threats were high.

[Insert Table 3.13]

[Insert Table 3.14]

3.5.3 Alternative measurements of default probability, secure-to-total debt ratio, and hostile takeover index

In the main tests, $Treat_i$ is a dummy variable, which equals one if firm i is in top 30% of default probability in January 2010, and zero otherwise. $Secure_i$ ($Takeover_i$) is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio (hostile takeover index) in 2010Q1 (2009). Managers might define default probability using a different cutoff or in a gradual fashion. Thus, I replace *Treat*$_i$, *Secure*$_i$, and *Takeover*$_i$ with continuous variables in a robust test. The results of leverage and debt structure remain similar to those in the main tests.

3.6 Conclusion

The relation between equity-based takeover threats and capital structure has been well studied. Previous research finds that firms use leverage to defend against equity-based hostile takeovers (e.g., Stulz, 1988, Denis and Denis, 1993; Berger, Ofek, and Yermack, 1997; Garvey and Hanka, 1999, etc.). I provide a new perspective on the rise of debt-based takeovers as a type of takeover threat to distressed firms. I find that the debt-based takeover threats have an opposite effect on capital structure and shareholder value.

Utilizing Radlax Gateway Hotel, et al., v. Amalgamated Bank as a natural experiment, I identify the causal relation between takeover threats from secured creditors and capital structure policies. After takeover threats from secured creditors increase, firms with high default probabilities reduce leverage, especially for those with high secured debt ratios or low equity-based takeover threats. Shareholder value of firms with high default probabilities decreases. Meanwhile, secured debt ratios decrease for firms with significant equity-based takeover threats, as managers are reluctant to deleverage. A high CEO pay-performance sensitivity encourages CEOs to reduce leverage in shareholders' interest. The results imply that takeover threats from secured creditors induce managers to reduce leverage to prevent activist secured creditors from intervening and acquiring a substantial part of the company. As managers need to adjust leverage oppositely to deter these two types of takeover threats, there exists a tradeoff in their capital structure decisions.

4.0 Chapter 4 Consumers as Liquidity Providers in the Retail Industry: An Empirical Analysis

During the coronavirus pandemic, gift cards are nothing short of a lifeline for some small businesses.

Jessica Dickler (CNBC, "Support small businesses with gift cards – but know the risks," May 6, 2020)

4.1 Introduction

Total prepaid card sales by US retailers were $140 billion in 2016[19]. The market of prepaid cards flourished because prepaid cards are popular gifts to reduce social risk (Waldfogel, 1993; Austin and Huang, 2012). Moreover, previous surveys and research show that retailers frequently and effectively use prepaid cards as a marketing tool to boost sales and engage consumers (Ernstberger, McDowell, and Parris, 2012) for two reasons. First, companies receive incremental spending. Seventy-four percent of the consumers spend an average of $59 more than what was on their prepaid cards. Second, prepaid cards acquire new customers. Forty-one percent of gift card recipients say that they would have never visited a particular store if they had not received a gift card[20]. Cheng and Cryder (2018) explain the effectiveness of prepaid cards as a promotion tool using double mental discounting that consumers mentally discount some gains multiple times to feel as if they spend less money than they actually do.

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[19] Alina Comoreanu, *Gift Card Market Size*, 2017
[20] FirstData, *2018 Prepaid Consumer Insights Study*

However, the literature pays little attention to the fact that firms receive up-front cash at the sale of prepaid cards and book revenue at redemption. The interval that exists between cash flows and revenues makes the prepaid card a type of short-term debt. I find that the average unredeemed prepaid card balance reported by US retailers is as large as $77.94 million and 7% of total liabilities. FirstData, a prepaid card program outsourcer, lists "interest from unredeemed balance" as one of the benefits[21]. This shows that retailers have taken the financing benefit of receiving upfront cash into consideration. Meanwhile, the mainstream media raises concerns that companies in non-financial industries (e.g., Starbucks, Google, Alibaba, Apple, Facebook, Amazon) are becoming competitors to commercial banks[22]. For example, Starbucks has a $1.6 billion stored value card liability at the end of 2018, which was more than the deposits at a number of financial institutions, including California Republic Bank, Mercantile Bank, and Discover Financial Services. Nearly one-third of the transactions are handled with the company's pre-paid cards. However, the "deposit" at Starbucks is neither insured by FDIC nor monitored by financial regulators. "*Starbucks is essentially an unregulated bank. If they decided to shed their coffee business, all the stored value in those cards is theirs to keep*.[23]" Therefore, a study of such financing effects of prepaid cards has important policy implications.

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[21] FirstData describes in *Gift Card Marketing Guide Best Practices* that, "You have possession of the dollars on the gift card from the time that the card is purchased. By depositing the funds into an interest-bearing account, you will be able to earn a return on your outstanding gift card balances."

[22] Simon Johnson, 2018, The First Bank of Starbucks; Tonya Garcia, 2016, Starbucks has more customer money on cards than many banks have in deposits; Marcus Wohlsen, 2014, The Next Big Thing You Missed: How Starbucks Could Replace Your Bank; Wayne Busch and Juan Pedro Moreno, 2014, Banks' New Competitors: Starbucks, Google, and Alibaba.

[23] Jason Snyder, global chief technology officer at Momentum, The Most Popular Mobile Payment App Isn't Apple Pay … It's Starbucks

Despite the importance of prepaid cards on retailers' balance sheets, there is, to my knowledge, no research about the financing effects of prepaid cards. This paper attempts to bridge this gap by addressing three previously ignored questions: What are the characteristics of the prepaid card balances of US retailers? Do retailers not only use prepaid cards as a marketing tool, but also take advantage of the financing benefits? Do retailers use prepaid cards to substitute other debt financing methods?

Answering these three questions is challenging for two reasons. First, there is no comprehensive dataset of prepaid cards. Second, it is difficult to disentangle the marketing motive and the financing motive of prepaid cards. The benefit of receiving up-front cash could be one of the reasons for retailers to sell prepaid cards, even with costly promotions. Alternatively, it could just be a side-effect of prepaid cards, which are primarily used as a marketing tool. I address the challenges in the following ways. First, I use a new hand-collected dataset from 10-K SEC filings of US retailers (51<Two-digit SIC<60) from 2004 to 2018. The dataset contains information on unredeemed prepaid card balances for 1,511 firm-year observations. Second, I use the CARD Act of 2009 as a natural experiment to demonstrate that the financing effect is an important determinant of prepaid card balances. The regulation put new restrictions on maturity dates and inactivity fees, thereby creating a positive (negative) shock to the effectiveness of the prepaid card as a financing (marketing) tool. The natural experiment allows me to conduct an analysis that compares the prepaid card balances and debt financing policies in firms with and without significant benefits of upfront cash.

I provide some new evidence about the financing effects of prepaid cards. First, the unredeemed prepaid card balance is a significant part of retailers' balance sheets. On average, the prepaid card balance is 3.4% of total assets and 7.0% of total liabilities. The size of unredeemed prepaid card balance is comparable to the size of retailers' trade credit, credit line, and cash holdings. Second, after a positive (negative) shock to the financing (marketing) effect of prepaid cards, retailers that value the opportunity to receive upfront cash (i.e., high interest expense ratios) increased prepaid card balances by 32.4% of the average Prepaid card balance/Total assets. Retailers that mostly used prepaid cards for consumer engagement or retention (i.e., in a competitive product market) reduced prepaid card balances by 44.1% of the average Prepaid card balance/Total assets. Third, prepaid card balances increase following covenant violations, as creditors use their acceleration and termination rights to increase interest rates and reduce the availability of credit. Fourth, after a positive (negative) shock to the financing (marketing) effect of prepaid cards, the amounts of small business loans decreased for retailers, relative to those for non-retailers. The result is more significant for loans with time-to-maturity less than a year. The time-to-maturity (cost) of small business loan increased (decreased) for retailers, compared to that for non-retailers. Retailers use prepaid cards to substitute short-term bank loans and trade credits.

My paper adds to the extant marketing and economic literature of prepaid cards. Some papers study social risk reduction by gifting prepaid cards (e.g., Waldfogel, 1993; Austin and Huang, 2012). Other papers find that prepaid cards lead to higher revenue as a marketing tool (Ernstberger, McDowell, and Parris, 2012; Cheng and Cryder, 2018). I study prepaid cards from a new perspective by documenting that the prepaid card is simultaneously used as a debt financing tool.

The paper is related to the trade credit literature because the prepaid card liability is a type of "reversed trade credit". The operation motive of trade credit has been widely understood. Schwartz (1974) introduces the financing motive of trade credit, which means that suppliers have cost advantages over financial institutions in offering credits to customers. Subsequent research extends the financing motive theory using information advantages (e.g., Smith, 1987; Biais, Gollier, and Viala, 1993), advantages in controlling the buyer (Cunat, 2007), and liquidation advantages (Mian and Smith, 1992). The logic of prepaid cards is similar. Previous literature documents that reducing the deadweight loss of gifting and boosting sales are motives for selling prepaid cards. In this paper, I provide evidence for the coexistence of the financing motive.

4.2 Hypotheses

In Figure 4.1, I analyze the financing effect of prepaid cards. Although the marketing motive can drive retailers to sell prepaid cards, I do not take it into account for simplicity. ABD is the supply curve of capital, as described in Hubbard (1997). AB is the total amount of internal capital. The cost of internal capital equals the market interest rate. The cost of capital starts to increase at B because of external capital market imperfections. r_0q_0C is the supply curve of capital from prepaid card buyers. q_0 is the maximum amount of prepaid cards sold at face value. The real interest rate of prepaid cards sold at face value is negative at r_0 because of the breakage income (i.e., The breakage income is recognized once the probability of the redemption of a gift card becomes remote.) and time value of money (e.g., inflation and interest rates). In other words, the retailers can raise q_0 at r_0 by selling gift cards at face value and receive upfront cash. If the firm wants to sell beyond q_0, it has to use discounts and promotions to attract new buyers, increasing the cost of prepaid cards (real interest rate).

Thus, the supply curve is upward-sloping from q_0 to C. The cost of prepaid cards depends on buyers' preferences. Buyers at the bottom of the supply curve are easy to attract (low cost of prepaid cards). Buyers at the top of the supply curve are difficult to attract and require better deals (high cost of prepaid cards).

[Insert Figure 4.1]

If it is costly to raise capital from the capital market, then the opportunity of receiving up-front cash is valuable. The financing benefit of an unredeemed prepaid card could be measured as the difference between the current interest expense and the cost of the prepaid card. Therefore, retailers with high interest expense ratios are more likely to pay high costs to sell additional prepaid cards for upfront cash. In Figure 4.1, retailers will use only prepaid cards to meet capital demand until the amount reaches q_B, at which costs of prepaid cards equal costs of internal capital. If retailers need more capital beyond q_B, they will start to raise capital through both prepaid cards and the capital market. I assume that the demand for capital remains the same. If the average interest expense increases from ABD to A'B'D', then retailers will only sell prepaid cards to meet capital demand until $q_{B'}$. Beyond $q_{B'}$, they will start to raise capital through both prepaid cards and the capital market. The increase in average interest expense from ABD to A'B'D' increases the prepaid card balance by at least $q_{B'} - q_B$. The slopes of r_0q_0C and ABD affect the growth of capital and prepaid cards. If the slope of r_0q_0C is steeper than that of ABD, then the capital raised from the capital market increases faster than prepaid cards and vice versa. However, the positive relation between the interest expense and prepaid cards remains unchanged as long as both supply curves are upward-sloping.

H1: The prepaid card balance is positively related to the average interest expense ratio.

An important characteristic of prepaid cards as a type of liability is that there is no predetermined "time-to-maturity." The time-to-redemption of prepaid cards significantly influences the effectiveness of prepaid cards as a marketing tool and a financing tool. Procrastination occurs for enjoyable activities because of people's higher discounting of costs but lower discounting of benefits (Soman, 1998; Trope and Liberman, 2003; Zauberman and Lynch, 2005). Therefore, activities with costs and benefits that occur with close temporal proximity appear to have a larger net benefit when imagined being completed in the future than when completed today (Shu and Gneezy, 2010). Limited windows are most effective at reducing this type of procrastination (Ariely and Wertenbroch, 2002).

Shu and Gneezy (2010) use experiments of gift card redemptions to show that the tendency to procrastinate applies to positive experiences with immediate benefits. They find that people procrastinate in redeeming gift cards with long deadlines more than those with short deadlines, resulting in overall lower redemption rates. If retailers intend to use prepaid cards to engage consumers, then they want a high redemption rate within a short period. Companies are likely to benefit from giving consumers short deadlines. However, the authors agree that companies benefit from high breakage incomes and may not be interested in high redemption rates in some cases. They suggest that public policy efforts to extend expiration dates may be good for the company in terms of higher satisfaction with the cards and lower redemption rates.

There exists a tradeoff between marketing and financing benefits when retailers choose expiration dates of prepaid cards. If retailers emphasize the marketing motive (i.e., acquire new customers, increase customer loyalty, and receive incremental spending), then they prefer short deadlines for prompt redemption and high redemption rate. If retailers value the financing benefits (i.e., delay redemption and low redemption rate), then they choose long deadlines. If there is a minimum requirement for expiration dates, then retailers that emphasize the financing (marketing) effect will increase (reduce) prepaid card balance.

H2a: After a positive shock to expiration dates of prepaid cards, prepaid card balances of retailers with high average interest expense ratios are larger than those of retailers with low average interest expense ratios.

H2b: After a positive shock to expiration dates of prepaid cards, prepaid card balances of retailers in a competitive market are smaller than those of retailers in a concentrated market.

In H1 and H2, the interest expense ratio is a proxy for financing benefits of receiving upfront cash through prepaid cards. However, interest expense and prepaid card balance might be correlated because of alternative explanations instead of financing benefits of unredeemed prepaid cards. To reinforce the conclusions drawn from the positive relation between interest expense ratios and prepaid card balances, I use an alternative proxy for financing benefits of unredeemed prepaid cards.

A sharp decline in the supply of credit could increase financing benefits of prepaid cards. Roberts and Sufi (2009) find that creditors use their acceleration and termination rights to increase interest rates and reduce the availability of credit (Sufi, 2009) in covenant violations. Net debt issuing activity experiences a sharp and persistent decline following debt covenant violations. Zhang (2018) documents that banks intervene in the borrowing firm following covenant violations and reduce trade credit. Raising capital through prepaid cards might be a way to circumvent debt covenants or lenders' intervention after covenant violations. Some debt covenants forbid retailers from borrowing more debt or issuing senior debt. Although prepaid cards have a similar financing effect as short-term debts, they are often not regarded as debt instruments. Therefore, I use debt covenant violations to replace the average interest expense ratio as the proxy for financing benefits of prepaid cards.

H3: The prepaid card balance increases following debt covenant violations.

If the prepaid card is partially used as a debt financing method, then it can substitute other debt financing methods. Garcia-Appendini and Montoriol-Garriga (2013) show that firms provide liquidity insurance to their clients when bank credit is scarce. Similarly, prepaid cards substitute more bank loans after they become more effective as a financing tool (average time-to-redemption increases, and redemption rate decreases). Therefore, the amounts of other debt financing methods (e.g., bank loan and trade credit) decrease in retailers after a positive shock to expiration dates of prepaid cards.

H4: After a positive shock to expiration dates of prepaid cards, the amounts of bank loan and accounts payable decreased more for retailers than for non-retailers.

4.3 Data and Summary Statistics

4.3.1 Data

I begin with a Compustat universe that contains U.S.-based firms in the retail trade industry (two-digit SIC code 51-59) between 2004 and 2018. The sample excludes firms with total assets below $5 million or less than five consecutive years of data. This yields a sample of 361 unique firms and 4,026 firm-year observations. I manually collect prepaid card balances from 10-K SEC filings. Although most retailers have prepaid card programs, some of them do not report the balance exclusively. The final sample has 160 unique firms and 1,511 firm-year observations, which represent 37.5% of the population.

Bank loan data is obtained from SBA 7(a) database. SBA 7(a) database contains loan information of small businesses with a loan amount below $5 million. The covenant violation data in 2004 – 2012 is from Roberts and Sufi (2009). The bankruptcy filing data is from the UCLA-LoPucki Bankruptcy Research Database. The stock CARs of retailers are calculated using Event Study by WRDS.

4.3.2 Summary Statistics

Table 4.1 contains summary statistics for the full sample. Retailers have an average unredeemed prepaid balance of $77.93 million. The balance represents 3.4% of total assets and 7% of total liabilities. To further show the significant financing effects of prepaid cards, I construct three measures. On average, the prepaid card balance-to-total credit lines ratio is 83.5%. The prepaid card balance-to-accounts payable ratio is 55.5%. The prepaid card balance-to-cash holdings ratio is 100.1%. The prepaid card balance might be large during the holiday season and small during other months. The average Prepaid card balance-to-Total liabilities is 9.1% for firms with fiscal years end on December 31 (503 firm-year observations). The average ratio decreases to 6.2% for firms with fiscal years end on January 31 (716 firm-year observations). Although the prepaid card balance is indeed larger during the holiday season, the average prepaid card balance is still a significant part of total liabilities at the end of January. Table 4.1 implies that prepaid cards have a significant financing effect, which is comparable to the financing effects of other short-term debt instruments.

Prepaid cards that are never redeemed could stay as liabilities indefinitely. To keep from having a liability on its balance sheets indefinitely, a retailer typically estimates a breakage amount and recognizes this into revenue. I collect breakage income from 10-K SEC filings as well. Many companies do not regularly record breakage income every year. In the sample, 573 out of 1,474 observations report breakage incomes. Some of the breakage incomes include cumulative breakage incomes in the previous years. The average breakage income is 4.9% of the net income[24].

Firm characteristics are defined as follows. Sales, Cash, Accounts payable, and PPENT are scaled by lagged Total assets. Firm size is measured as the natural logarithm of Total assets. Leverage is defined as Long-term debt plus Current liabilities divided by Total assets. ROA is Net income divided by Total assets. I calculate Profit margin as (Sales-Cost of goods sold)/Sales. Altman Z-score is a proxy for financial distress, which is calculated as 1.2×(Working capital/Total assets) + 1.4× (Retained earnings/Total assets) + 3.3×(EBIT/Total assets) + 0.6 ×(Market value of equity/Total liabilities) + 0.999× (Net sales/Total assets). HHI is calculated for each three-digit SIC code. I winsorize all financial variables at the 1st and 99th percentiles.

[Insert Table 4.1]

[24] Retailers can recognize breakage incomes using remote method or redemption pattern method. Remote method: the breakage income is recognized once the probability of the redemption of a gift card becomes remote. Redemption pattern method: the breakage income is recognized on a pro-rated basis determined by the redemption pattern of the outstanding gift cards redeemed. The ASC 606 requires companies to use redemption pattern method after 2018. However, both methods require some estimates.

Table 4.2 shows the trend of prepaid card balance over time. The average prepaid card balance increases from $45.6 million to $149.2 million over 14 years. CEB Tower Group documents a similar increase rate of US gift card market size. The balance was low in 2008 and 2009 during the financial crisis. Prepaid card liability/Cash, Prepaid card liability/Line of credit, and Prepaid card liability/accounts payable are high in 2008. Although the prepaid card balance was low because of the demand reduction, the magnitude is much smaller than the magnitudes of decreases in cash, credit line, and accounts payable. Prepaid card balance/Accounts payable grows steadily. Prepaid card balances, as “reversed” trade credit, have started to become important relative to traditional trade credits.

[Insert Table 4.2]

Table 4.3 shows prepaid card balances by two-digit SIC code. Prepaid cards are commonly used in some industries, while are sporadically used in other industries. The highest use of prepaid cards is in Eating & Drinking Places and Miscellaneous Retail. The average Prepaid card balance/Total assets are 4.4% in both industries. The lowest Prepaid card balance/Total assets is in Food Stores and Automotive Dealers & Service Stations. The differences in Prepaid card balance/Total assets could be explained by the nature of the products or services or product market competition.

[Insert Table 4.3]

4.4 Empirical Design

4.4.1 Identification Strategy

Although I expect that both financing and marketing motives drive retailers to sell prepaid cards, it is challenging to disentangle the financing motive and the marketing motive. I utilize the Credit Card Accountability Responsibility and Disclosure Act of 2009 (CARD Act) as a natural experiment to address this challenge.

The CARD Act primarily instituted new consumer protection and disclosure requirements for credit cards. The goal was to protect consumers against unfair fees and interest[25]. Besides new restrictions on credit cards, Regulation E of the CARD Act put new restrictions on all gift cards sold on or after August 22, 2010. (1) Gift cards cannot expire for at least five years after they were last loaded with money. (2) Inactivity (dormancy) fees may not be imposed unless the card has been unused for at least 12 months. The requirements of expiration dates and inactivity fees require all prepaid cards to have long deadlines and low inactivity fees. Thus, the CARD Act is a positive shock to expiration dates of prepaid cards.

As discussed in Section 4.2, this increases consumers' tendency to procrastinate and results in delayed redemptions and low redemption rates (Shu and Gneezy, 2010). If a prepaid card is primarily used as a marketing tool to engage consumers, then the retailer wants consumers to redeem it sooner. If a prepaid card is mainly used as a financing tool for

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[25] Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015) analyze the effect of the CARD Act on credit card holders, using a panel data set covering 160 million credit card accounts and a difference-in-differences research design. In this paper, I only focus on Regulation E of the CARD Act, which puts new restrictions on prepaid cards, gift certificates, and store gift cards. Financial institutions with credit card business can be affected by the CARD Act. To address this concern, I exclude firms in the financial service sector.

upfront cash, then the retailer hopes consumers to delay redemption or never redeem. Therefore, the CARD Act is a negative shock to the effectiveness of prepaid cards as a marketing tool and a positive shock to the financing benefits of prepaid cards.

I verify that the CARD Act is indeed a positive shock to the financing effect of gift cards using an event study of stock returns. The information about the expiration dates of gift cards sold by each retailer is unavailable. According to Shu and Gneezy (2010), retailers that mainly use prepaid cards as a marketing tool are more likely to originally have short expiration dates and be forced to increase expiration dates after the CARD Act. Retailers that mainly use gift cards as a financing tool might already have long expiration dates and are unaffected by the CARD Act. Therefore, the CARD Act is overall more beneficial or less harmful to retailers with high interest expense ratios (in a concentrated market) than retailers with low interest expense ratios (in a competitive market).

The bill was first passed by the House on April 30, 2009. The Senate followed suit and passed an amended version on May 19, 2009. The House passed the amended bill on May 20, 2009. The bill was signed into law on May 22, 2009. Because the event on April 30, 2009, is the most unexpected one compared to the later events, I conduct an event study around April 30, 2009, in Table 4.4. To account for the possibility of information leakage prior to the event or a lag in the information being incorporated into prices, I also analyze CARs in progressively wider windows centered on the event date. I report stock CARs for the full sample, subsamples of high and low interest expense ratios, and subsamples of concentrated and competitive markets. Firms with high (low) interest expense ratios are those with above (below) median interest expense ratios in 2008. Firms in a concentrated (competitive) market are those with HHI>0.2 (HHI<0.2) in 2008. The difference between high and low interest expense ratios (concentrated and competitive) is reported using two-sample t-tests.

CARs are significantly positive in [0] for all retailers. The CARD Act is overall positive news to shareholders. The level of significance and magnitude of CARs for retailers with high interest expense ratios are larger than those for retailers with low interest expense ratios. The CARD Act is significantly more beneficial to retailers with high interest expense ratios. Stock CARs are significantly positive in concentrated markets and insignificant in competitive markets. The CARD Act is significantly more beneficial to retailers in concentrated markets than in competitive markets. The results of the event study suggest that the CARD Act is a positive shock to the financing effect of prepaid cards and a negative shock to the marketing effect of prepaid cards.

[Insert Table 4.4]

4.4.2 Econometric Model

I use a Difference-in-Differences analysis to examine the causal relation between the financing motive and prepaid card balances.

$$\left(\frac{Prepaid\ card\ balance}{Total\ assets}\right)_{i,t} = \alpha_i + \delta_t + \beta_0 + \beta_1 * Treat_i * Aft_t + \gamma * X_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

I use two variables to identify treatment groups. $Interest2009_i$ is a dummy variable, which equals one if firm i has above median average interest expense ratio in 2009, and zero otherwise. $Compete2009_i$ is a dummy variable, which equals one if HHI of firm i was in the bottom 30% in 2009, and zero otherwise. Aft_t is a dummy variable, which equals one starting from 2010, and zero otherwise. I control for firm characteristics, including interest expense, Altman Z-score, sales, size, cash, accounts payable, leverage, ROA, PPENT, profit margin, cash cycle, and firm age. All independent variables are at the end of the previous year. Standard errors are clustered at the firm level, and all regressions include firm and year fixed effects. $Treat_i$ and Aft_t are dropped because of collinearity.

4.5 Main Results

4.5.1 Baseline regressions of the prepaid card balance

Table 4.5 presents the estimation results of baseline regressions of prepaid card balances. The dependent variable is (Prepaid card balance/Total assets)$_{i,t}$. Control variables are as described in Section 4.4.2. I include firm fixed effects and year fixed effects. Standard errors are clustered by firm. In Column 1, the coefficient of (Interest expense/Total liabilities)$_{i,t-1}$ is significantly positive. Consistent with H1, the prepaid card balance is positively related to the average interest expense ratio. One percent increase in (Interest expense/Total liabilities)$_{i,t-1}$ is related to 0.13% increase in (Prepaid card balance/Total assets)$_{i,t}$. Coefficients of (Cash/Total assets)$_{i,t-1}$ and (Accounts payable/Total assets)$_{i,t-1}$ are significantly negative, suggesting that firms with less access to cash holdings and trade credits have larger prepaid card balances. This implies that prepaid cards might substitute trade credits and internal capital. I further test this inference in Table 4.7.

The positive association between the prepaid card balance and the average interest expense should only be significant in concentrated product markets. First, the marketing motive of prepaid cards is more important in a competitive product market than in a concentrated product market as engaging consumers is a pressing task in competitive markets. The financing benefit should be similar in both types of markets. Therefore, the financing benefit is a dominating determinant of selling prepaid cards in a concentrated market. Second, the supply curve of capital from prepaid cards in Figure 4.1 reflects a price discrimination strategy, which is more effective with monopoly power. Traditional microeconomic theory predicts a negative relation between competition and price dispersion (Gerardi and Shapiro, 2009). If a retailer is a price taker in a perfectly competitive market, then it is difficult to extract economic profit by selling its products (including prepaid cards). Extracting financing benefits from unredeemed prepaid cards is even more difficult. Column 2 tabulates supporting result. $\text{Concentrate}_{i,j,t-1}$ is a dummy variable, which equals one if HHI>0.2 for firm i in industry j (three-digit SIC code) in t-1, and zero otherwise. The coefficient of $(\text{Interest expense/Total liabilities})_{i,t-1}$ is insignificant, while the coefficient of $\text{Concentrate}_{i,j,t-1} \times (\text{Interest expense/Total liabilities})_{i,t-1}$ is significantly positive.

[Insert Table 4.5]

4.5.2 Prepaid card balances and the CARD Act of 2009

As discussed in Section 4.4, I utilize the CARD Act of 2009 as a natural experiment to disentangle the impacts of the financing and marketing benefits on prepaid card balances. It creates a positive (negative) shock to the effectiveness of prepaid cards as a financing (marketing) tool. I conduct a DID analysis to compare high and low interest expense ratios (concentrated and competitive) retailers around the CARD Act.

A core assumption of DID is that there is no pre-existing differential trend between treated and control firms. Under this assumption, any difference after the treatment is the result of the treatment. The absence of a pre-treatment parallel trend leads to biased estimates of the causal effect. Figure 4.2 shows the parallel trend of prepaid card balances of firms with high and low interest expense ratios in 2009. The event date t=0 is 2010. I plot the year-by-year differences in prepaid card balance of firms with high and low interest expense ratios relative to those in 2004 (t = -6). Prior to 2010, both groups had similar trends. After 2010, the average differences become significantly larger than those in 2004. The difference in 2010 (t=0) is not significantly different from those in 2004 because the regulation took effect on August 22, 2010. The effect of the regulation is not prominent at the end of 2011. Figure 4.2 supports the pre-treatment parallel trend assumption of DID analysis.

[Insert Figure 4.2]

Figure 4.3 shows the parallel trend of prepaid card balances of firms in competitive and non-competitive markets. Before 2010 (t=0), the differences in prepaid card balances between competitive and non-competitive groups are not significantly different from those in 2004 (t= -6). After 2012 (t=2), the average differences become significantly smaller than those in 2004. Similar to Figure 2, the difference in 2010 (t=0) is not significantly different from those in 2004 because the regulation took effect at the end of 2010. The difference in 2011 (t=1) is still not significantly different from those in 2004. However, the coefficient of $Compete2009_i \times Year\ 2011_t$ is -0.006 (P value=0.16) is significantly lower than those in previous years. Therefore, there was a sharp decline in the difference in prepaid card balances between competitive and non-competitive groups in 2011.

[Insert Figure 4.3]

Table 4.6 tabulates the estimation results of equation (1). In Column 1, the coefficient of $\text{Interest2009}_i \times \text{Aft}_t$ is significantly positive, suggesting that the difference in prepaid card balance between retailers with high and low interest expense ratios significantly increased after 2009. Consistent with H2a, after a positive shock to the financing effect of prepaid cards, retailers with high interest expense ratios had larger prepaid card balances relative to other retailers. Retailers with above-median interest expense increased Prepaid card balance/Total assets by 0.011, which is 32.4% of the average Prepaid card balance/Total assets. In Column 2, the coefficient of $\text{Competitive2009}_i \times \text{Aft}_t$ is significantly negative. Consistent with H2b, retailers in competitive markets are likely to use prepaid cards as a marketing tool. After a negative shock to the marketing effect of prepaid cards, they reduced prepaid card balances relative to other retailers. Retailers in competitive markets reduced Prepaid card balance/Total assets by 0.015, which is 44.1% of the average Prepaid card balance/Total assets. Results of Table 4.6 confirm H2a and H2b, suggesting that the financing benefit is one of the reasons for some retailers to sell prepaid cards.

[Insert Table 4.6]

I examine whether retailers increase prepaid cards when they do not get access to similar short-term debt financing methods and internal capital. Trade credit is a similar type of short-term liabilities for two reasons. First, both trade credit and prepaid cards are related to the upstream or downstream firms. The unredeemed prepaid card is considered as “reversed trade credit”. Second, they are both short-term liabilities. The average duration of trade credit is 59.2 days (Klapper, Laeven, and Rajan, 2012). A market survey indicates that only 30 percent of recipients use a gift card within a month of receiving it[26]. I investigate whether firms with low accounts payable and cash holdings in 2009 increased prepaid cards after the positive shock to financing benefits. Table 4.7 reports the estimation results. $Payable2009_i$ is a dummy variable, which equals one if firm i has above-median accounts payable in 2009, and zero otherwise. $Cash2009_i$ is a dummy variable, which equals one if firm i has above-median cash holdings in 2009, and zero otherwise. Coefficients of $Payable2009_i \times Aft_t$ and $Cash2009_i \times Aft_t$ are negative in both regressions. Retailers with large trade credits and cash holdings did not value the financing benefits of prepaid cards. After a positive (negative) shock to the financing (marketing) effect, they have smaller prepaid card balances compared to other retailers.

[Insert Table 4.7]

4.6 The Substitution Effect

In Section 4.5.2, I find that the financing benefit of receiving upfront cash is one of the reasons for retailers to sell prepaid cards. In this section, I study whether prepaid cards substitute other financing methods, including bank loans and trade credits. I use the small business bank loan data from SBA 7(a) database to test the change in bank loans. However, the implications apply to both public and small firms.

Table 4.8 tabulates the change in small business loans around the CARD Act. The dependent variable is the natural logarithm of the amount of small business loan. $Retail_j$ is a

[26] S. J. Dubner And S. D. Levitt (2007), The Gift-Card Economy, The New York Times.

dummy variable, which equals one if the borrower of loan j is in the retail industry, and zero otherwise. Aft_t is a dummy variable, which equals one if loan j was approved after September 2010, and zero otherwise. Column 1 reports the baseline regression result. The coefficient of $Retail_j \times Aft_t$ is significantly negative, which suggests that the loan amount of retailers decreased after the CARD Act, compared to the loan amount of non-retailers. Consistent with H4, retailers relied less on bank loans after a positive shock to the financing effect of prepaid cards.

A vital difference between prepaid cards and bank loans is that financing through prepaid cards does not have a predetermined maturity date. Although previous literature suggests that expiration dates influence time-to-redemption and redemption rate (e.g., Ariely and Wertenbroch, 2002; Shu and Gneezy, 2010), consumers have the latitude to redeem prepaid cards any time before the expiration date. Meanwhile, retailers do not have to repay interest and principle before the predetermined date. Public retailers do not canonically disclose the average time-to-redemption and redemption rate. In Column 2, I conduct an analysis to investigate whether prepaid cards primarily substitute bank loans with a certain range of time-to-maturity. One $year_j$, One-to-five $year_j$, and Five-to-ten $year_j$ are dummy variables which equal one if time-to-maturity of loan j is less than 1 year, 1-5 years, and 5-10 years, respectively. The coefficients of $Retail_j \times Aft_t \times$ One $year_j$, $Retail_j \times Aft_t \times$ One-to-five $year_j$, and $Retail_j \times Aft_t \times$ Five-to-ten $year_j$ are -0.482 (P-value=0.000), -0.053 (P-value=0.000), and -0.010 (P-value=0.387) respectively. The level of significance and magnitude are higher for loans with short time-to-maturity than for loans with long time-to-maturity. The amounts of loans with short time-to-maturity decreased more than the amounts of loans with long time-to-maturity after the CARD Act. Column 2 of Table 4.8 suggests that prepaid cards primarily substitute short-term bank loan as a debt financing method.

[Insert Table 4.8]

In Table 4.9, I tabulate the changes in time-to-maturity and cost of small business loans. The dependent variables are the natural logarithm of the number of months to maturity and the natural logarithm of the interest rate. In Column 1, the coefficient of $Retail_j \times Aft_t$ is significantly positive. The time-to-maturity of small business loans of retailers increased after the CARD Act, compared to the time-to-maturity of small business loans of non-retailers. As discussed in Table 4.8, prepaid cards can substitute short-term loans instead of long-term loans. Retailers will borrow from banks when they require a long time-to-maturity, but consumers generally redeem within a short period. After the CARD Act, the average time-to-redemption of prepaid cards increased, allowing prepaid cards to substitute bank loans with longer time-to-maturity. The bank loans that still cannot be substituted by prepaid cards have even longer time-to-maturity. Therefore, the time-to-maturity of small business loans for retailers increased after the CARD Act.

In Column 2, the coefficient of $Retail_j \times Aft_t$ is significantly negative. The result is also consistent with the substitution effect of prepaid cards. Given the same time-to-maturity, retailers will use prepaid cards to replace bank loans when costs of prepaid cards are lower than loan interest rates. After the CARD Act, more prepaid cards can substitute bank loans. Bank loans with relatively high interest rates can be substituted, while the remained bank loans that are not substituted have low costs. Thus, the costs of bank loans for retailers decreased, compared to those for non-retailers.

[Insert Table 4.9]

As discussed in Section 4.5.2, trade credits are similar short-term liabilities to prepaid cards. Retailers with large amounts of accounts payable increased smaller prepaid card balances after the CARD Act. In Table 4.10, I report the change in trade credits around the CARD Act. The sample includes all Compustat firms, excluding firms in the Finance, Insurance, and Real Estate industry. $Retail_i$ is a dummy variable, which equals one if firm i is in the retail industry, and zero otherwise. The coefficient of $Retail_i \times Aft_t$ is significantly negative. Retailers have lower accounts payable relative to firms in other industries after the CARD Act. After a positive shock to the financing effect of prepaid cards, retailers replaced trade credits with prepaid cards.

[Insert Table 4.10]

4.7 Additional Results

4.7.1 Prepaid card balances and debt covenant violations

As discussed in H3, the average interest expense ratio is not a perfect measure of the benefit of receiving upfront cash. It might correlate with a third variable, which actually drives the change in prepaid card balances. To reinforce the conclusions, I use the covenant violation as an alternative proxy for the benefit of receiving upfront cash. I follow Sufi (2009) to examine the effect of covenant violations on prepaid card balances by estimating equation (2). I include indicators that identify two years before and four years following covenant violations. Standard errors are clustered at the firm level, and all regressions include firm and year fixed effects.

$$\left(\frac{Prepaid\ card\ balance}{Total\ assets}\right)_{i,t}$$
$$= \alpha_i + \delta_t + \beta_0 + \beta_1 * Violation_{i,t+1} + \beta_2 * Violation_{i,t} + \beta_3 * Violation_{i,t-1} + \beta_4$$
$$* Violation_{i,t-2} + \beta_5 * Violation_{i,t-3} + \beta_6 * Violation_{i,t-4} + \gamma * X_{i,t-1}$$
$$+ \varepsilon_{i,t} \qquad (2)$$

Table 4.11 presents estimation results of equation (2). The coefficients of Covenant violation$_{i,t+1}$ and Covenant violation$_{i,t}$ are insignificantly different from zero. Coefficients of Covenant violation$_{i,t-1}$ to Covenant violation$_{i,t-4}$ are significantly positive. Consistent with H3, retailers do not significantly increase prepaid card balances before or during the year of covenant violations but increase prepaid card balances following covenant violations. The test verifies the conclusions drawn from the main results in Section 4.5.

[Insert Table 4.11]

4.7.2 Prepaid card balances and bankruptcy

When the retailer is close to bankruptcy filings, there might be technical or payment defaults, and standard financing options are no longer available. The financing benefits of prepaid cards are maximized for two reasons. First, unredeemed prepaid cards are categorized as unsecured debt in bankruptcy. Nevertheless, costs of prepaid cards could be lower than costs of other unsecured debts because the claims might be treated as a top priority in bankruptcy. Specifically, the debtor sometimes seeks the permission of the court to continue honoring prepaid cards after bankruptcy filings. Attorneys general often argue in favor of consumers being given priority treatment in bankruptcy (Rosen, 2015). The possible priority treatment in bankruptcy results in lower ex ante costs of prepaid cards. Second, consumers are well diversified and uninformed, compared to other creditors of the retailer. The marginal cost for an individual consumer to collect and analyze financial information far exceeds the marginal benefit. Costs of prepaid cards are not highly sensitive to the bankruptcy risk, compared to costs of other debts.

Some retailers deliberately offer discounts to sell more prepaid cards before bankruptcy filings. For example, in bankruptcy of Radioshack, Texas Attorney General Office claimed that "RadioShack knew after the 2014 holiday season ended that it would be declaring bankruptcy soon, and that gift cards they had issued would lose their value at the time of the bankruptcy or shortly afterward, yet sold the cards anyway [27]." Toys "R" Us was able to increase its gift card balance to $233 million in January 2017 ($222 million, $205 million, $199 million in the previous three years), even though it filed for bankruptcy in September 2017. In the appendix, I provide a list of promotions related prepaid cards of Toys "R" Us in recent years collected from deal information websites. Before 03/31/2016, gift cards were sold by Toys "R" Us at 10% - 30% off. Starting from 08/24/2016, Toys "R" Us frequently offered 50% off. Even two months before the bankruptcy filing, Toys "R" Us still sold its gift cards at 50% off.

Figure 4.4 shows the trend of Prepaid card balance/Total assets before bankruptcy filings. The sample is limited to firms that ultimately file for bankruptcy. The average prepaid card balance gradually decreases from year -8 to year -3. From year -3 to year -1, the average Prepaid card balance/Total assets increases from 0.020 to 0.027.

[Insert Figure 4.4]

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[27] https://consumerist.com/2015/12/04/people-holding-onto-radioshack-gift-cards-can-now-file-refund-claims/

I also use Penalized Maximum Likelihood Estimation to examine the relation between bankruptcy filings and prepaid card balances. The dependent variable $\text{Bankruptcy}_{i,t}$ is a dummy variable, which equals one if firm i files for bankruptcy in year t. The financial data of many retailers stops updating before bankruptcy filing dates. To address for the mismatch, I define $\text{Bankruptcy}_{i,t}$ equals one if t is the last observation of firm i in Compustat and firm i files for bankruptcy within two years. Because $\text{Bankruptcy}_{i,t}$ equals one in only 14 out of 1,489 firm-year observations, the small-sample bias of conventional logistic regression is serious (King and Zeng, 2001). I use the Penalized likelihood regression (Firth-type) to correct the small sample bias. I include prepaid card balance from t-1 to t-3 as independent variables and follow Jones and Hensher (2004) to control for firm characteristics. In Table 4.12, the coefficient of Prepaid card balance/Total $\text{assets}_{i,t-1}$ is significantly positive. If firm i has a larger prepaid balance in year t-1, then it is more likely to file for bankruptcy in year t. The evidence in Figure 4.4 and Table 4.12 suggests that the prepaid card balance jumps shortly before bankruptcy filings.

[Insert Table 4.12]

4.8 Conclusion

The literature and survey in marketing argue that the prepaid card is a standard tool to boost sales. Meanwhile, the unredeemed prepaid card balance is reported as short-term liabilities on the balance sheets. The financing benefit of prepaid cards has become noteworthy in daily life. However, the extant literature has not discussed the financing effect of prepaid cards. I provide the first comprehensive study of the financing effects of prepaid cards of US retailers. It shows that retailers value the opportunity of receiving upfront cash flows through selling prepaid cards.

There are four main findings in this article. First, unredeemed prepaid card balance accounts for 3.4% of total assets and 7.0% of total liabilities. Prepaid cards inevitably have a considerable financing effect on retailers. Second, retailers with high interest expense ratios increased prepaid card balances after a positive shock to the financing effect of prepaid cards. Retailers in competitive markets decreased prepaid card balances after a negative shock to the marketing effect of prepaid cards. Third, the prepaid card balance increases following debt covenant violations. The average prepaid card balance jumps one year before bankruptcy filings when the financing benefit hits its peak. Fourth, prepaid cards substituted short-term bank loans and accounts payable after a positive shock to the financing effect of prepaid cards.

The paper exhibits the trend that the lines between industry sectors blur and non-banks are capturing more and more of the banking value chain. For example, Paypal is a strong competitor in the payment area. T-mobile has launched a new checking service. Whether to raise or lower regulatory barriers to these new players is an important question facing policymakers. My paper provides evidence for the financial features of non-financial tools that are used in non-financial business sectors. It calls financial regulators' attention to these new phenomena.

Appendix A.1 Appendix of Chapter 2

Appendix A.1.1 The Marblegate Asset Management et al. v. Education Management Corp Ruling in 2014

There is a debate on whether bond exchange offers with exit consent violate Section 316(b) of the TIA in out-of-court restructurings. On one hand, no payment term of the original bond is directly changed. On the other hand, it is considered unfair because it forces bondholders to accept unwanted payment terms of new bonds (e.g., Coffee and Klein, 1991). As the junk bond market flourished in the 1980s, exit consent became common as an out-of-court restructuring method. Coercive bond exchange offers were widely considered legitimate because they were upheld by highly respected judge William Allen in 1986, the Chancellor of the Delaware Court of Chancery.

Section 316(b) of the TIA was only brought to a court to challenge an exit consent transaction for the first time in 1992[28]. The SDNY argued that Section 316(b) "does not affect or alter the substance of a noteholder's right to payment of principal and interest . . . and cannot 'override'" an indenture's subordination provisions. In 1999, the SDNY ruled differently that the exit consent exchange offer was in violation of the TIA and struck down

28 *UPIC & Co. v. Kinder-Care Learning Centers, Inc.*, 793 F. Supp. 448 (SDNY 1992)

the transaction [29]. Nonetheless, after the 1999 SDNY decision, people still generally followed the Delaware court decision and considered exit consent as a legitimate transaction.

Exit consent bond exchange was rarely challenged under the TIA until the recent ruling of *Marblegate Asset Management et al. v. Education Management Corporation.* The ruling significantly increased uncertainty in coercive bond exchange in ways favoring holdout creditors. Education Management Corporation (EMC) is a Pittsburgh-based operator of for-profit post-secondary educational institutions. Facing financial distress, EMC restructured $1.5 billion outstanding debt of its subsidiary, Education Management LLC. The debt included $1.15 billion in secured term loans, $150 million in revolving loans, and $220 million in unsecured notes under the TIA. All debt was guaranteed by EMC. There are two options of the Proposed Restructuring Agreement.

Under the first option, if 100% debtholders consent, then revolving loan creditors would receive full cash payment of $150 million and other secured lenders would receive debt and equity worth $631 million. Unsecured noteholders would receive 23.5% of EMC's common stocks. After failing to get 100% consent in the first voluntary exchange plan, EMC turned to the second option. (1) Secured lenders would release EMC's parent guaranty of the secured loans, automatically releasing EMC's parent guaranty of unsecured notes according to the indenture. (2) Secured lenders foreclose on 'substantially all of the assets' of Education Management LLC. (3) Secured lenders immediately sell these assets back to a new subsidiary of EMC, which would repay consenting creditors.

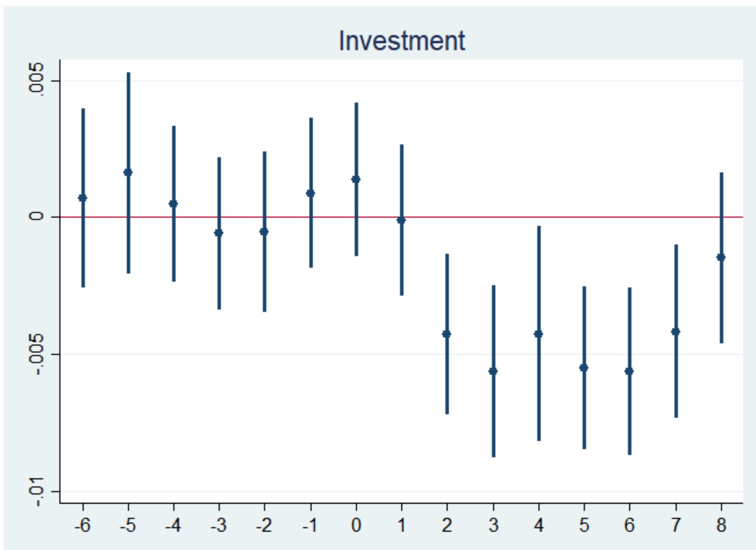
29 *Federated Strategic Income Fund v. Mechala Grp. Jam. Ltd.,* No. 99 CIV 10517 HB, 1999 WL 993648, at (SDNY Nov. 2, 1999)

Some dissenting noteholders sued EMC in SDNY that the proposed restructuring violated Section 316(b). The Plaintiffs complained that exit consent left them a debtor with no asset and parent guaranty to satisfy their claims. The transaction impaired dissenting noteholders' practical ability to receive payment. On December 30^{th}, 2014, the court concluded that the transaction violated the TIA.

Appendix A.1.2 Figures of Chapter 2

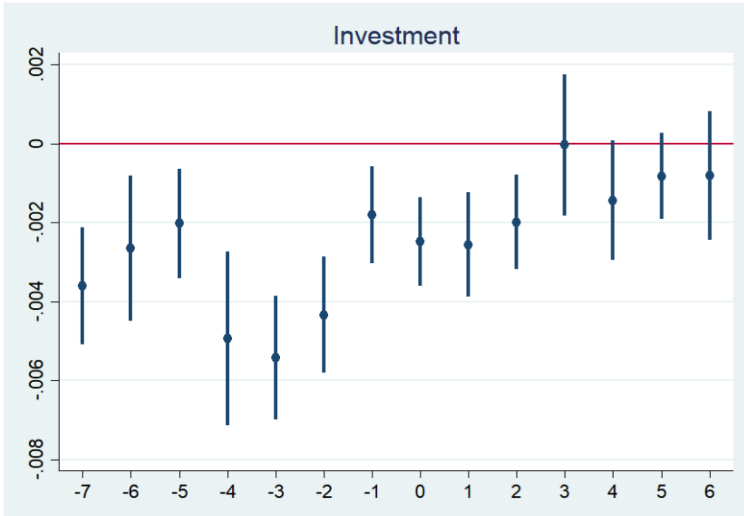
Figure 2. 1 Average difference in investment between treated and control groups in distressed firms

Panel A: The 2014 EMC ruling



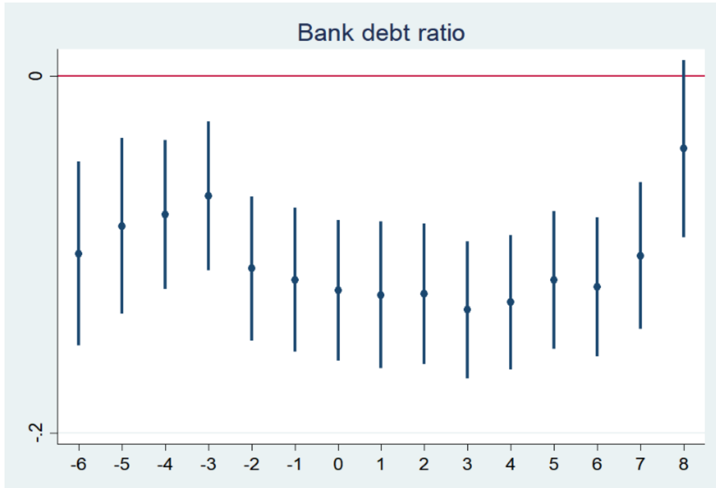
The figure shows coefficients of interactions between quarter dummy variables and treat dummy variable and 95% confidence intervals of coefficients. The sample is limited to distressed firms (defined using default probability in November 2014) from 2013Q1 to 2016Q4. The event date 0 is 2014Q4. The treated group includes firms with outstanding bonds with an offering amount of $10 million or above (offering date before November 30th, 2014 and maturity date after December 31st, 2016).

Panel B: The 2017 EMC ruling



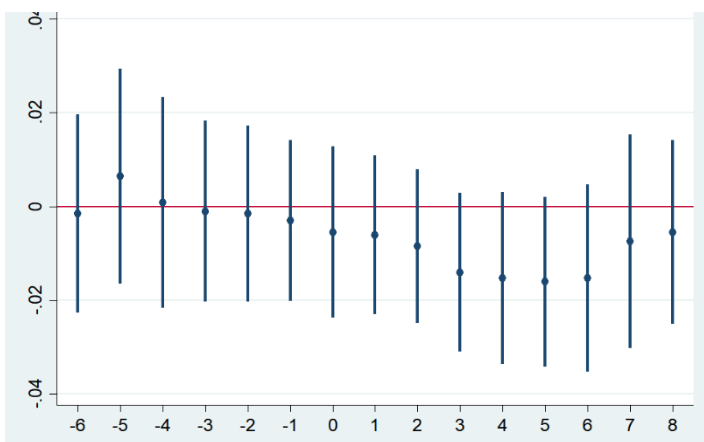
The figure shows coefficients of interactions between quarter dummy variables and treat dummy variable and 95% confidence intervals of coefficients. The sample is limited to distressed firms (defined using default probability in December 2016) from 2015Q1 to 2018Q4. The event date 0 is 2017Q1. The treated group includes firms with outstanding bonds with an offering amount of $10 million or above (offering date before December 31st, 2016 and maturity date after December 31st, 2018).

Figure 2.2 Average difference in bank debt ratio between treated and control groups in distressed firms



The figure shows coefficients of interactions between quarter dummy variables and treat dummy variable and 95% confidence intervals of coefficients. The sample is limited to distressed firms (defined using default probability in November 2014) from 2013Q1 to 2016Q4. The event date 0 is 2014Q4. The treated group includes firms with outstanding bonds with an offering amount of \$10 million or above (offering date before November 30th, 2014 and maturity date after December 31st, 2016).

Figure 2.3 Average difference in intangible assets between treated and control groups in distressed firms



The figure shows coefficients of interactions between quarter dummy variables and treat dummy variable and 95% confidence intervals of coefficients. The sample is limited to distressed firms (defined using default probability in November 2014) from 2013Q1 to 2016Q4. The event date 0 is 2014Q4. The treated group includes firms with outstanding bonds with an offering amount of \$10 million or above (offering date before November 30th, 2014 and maturity date after December 31st, 2016).

Appendix A.1.3 Tables of Chapter 2

Table 2.1 Number of Chapter 11 filings by year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Total	Treated	Chapter 11 among treated firms	% of Chapter 11 among treated firms	Control	Chapter 11 among control firms	% of Chapter 11 among control firms
2013	426	49	0	0%	377	13	3%
2014	433	50	1	2%	383	19	5%
2015	442	50	0	0%	392	28	7%
2016	461	72	9	13%	389	33	8%
2017	443	44	5	11%	399	18	5%
2018	437	46	1	2%	391	18	5%

The SDNY District Court ruled against coercive bond exchange in December 2014.

The Second Circuit reversed the 2014 ruling in January 2017.

This table shows the number of Chapter 11 bankruptcy filings by year. My sample includes distressed firms with top 20% default probabilities at the beginning of the year. I collect Chapter 11 filings from the UCLA-LoPucki Bankruptcy Research Database. Distressed firms are divided into treated and control groups. Treated firms are those with outstanding public bonds under the TIA. Control firms are those without outstanding public bonds under the TIA.

Table 2.2 Univariate tests on stock CARs

Panel A: Stock CARs around December 30th, 2014

Event window	Non-distressed	Distressed	Distressed minu Non-distressed
[-5,5]	0.000	-0.028***	-0.028*
[-3,3]	0.000	0.001	0.002
[-1,1]	0.000	0.007*	0.006
[0]	-0.002***	-0.002	0.000

Panel B: Stock CARs around January 17th, 2017

Event window	Non-distressed	Distressed	Distressed minus Non-distressed
[-5,5]	0.005**	0.012	0.006
[-3,3]	0.007***	0.029***	0.022**
[-1,1]	0.004***	0.011*	0.007
[0]	0.005***	0.030***	0.025***

Table 2.2 shows univariate tests of stock CARs of treated firms around the 2014 EMC ruling and 2017 EMC ruling. All firms in the sample are split into distressed and non-distressed groups. Abnormal returns are estimated using the Fama-French three-factor model. Estimation window is [-200, -50]. Differences in CARs between distressed and non-distressed firms are reported, controlling for the within-industry and within-state correlations. Panel A shows univariate tests of stock CARs around the 2014 EMC ruling (December 30th, 2014) in different event windows. Treated firms are those with outstanding bonds with an offering amount of $10 million or above (with offering date before November 30th, 2014 and maturity date after December 31st, 2016). Distressed firms are those in the top default probability quintile in November 2014. The rest of the firms are non-distressed. Panel B shows univariate tests of stock CARs around the 2017 EMC ruling (January 17th, 2017) in different event windows. Treated firms are those with outstanding bond with an offering amount of $10 million or above (with offering date before December 31st, 2016 and maturity date after December 31st, 2018). Distressed firms are those in the top default probability quintile in December 2016. The rest of the firms are non-distressed. *, **, *** Statistical significance in two-tailed t-tests at the 10%, 5%, 1% levels, respectively.

Table 2.3 Univariate tests on bond CARs

Panel A: Bond CARs around December 30th, 2014

Event window	Non-distressed	Distressed	Distressed minus Non-distressed
[-5,5]	0.002	0.015***	0.014***

Panel B: Bond CARs around January 17th, 2017

Event window	Non-distressed	Distressed	Distressed minus Non-distressed
[-5,5]	-0.015***	-0.021***	-0.006*

Table 2.3 shows univariate tests of bond CARs of treated firms around the 2014 EMC ruling and 2017 EMC ruling. All firms in the sample are split into distressed and non-distressed groups. Abnormal return is estimated using the Fama-French five-factor model. Estimation window is [-200, -50]. Differences in CARs between distressed and non-distressed firms are reported, controlling for the within-industry and within-state correlations. Panel A shows univariate tests of bond CARs around the 2014 EMC ruling (December 30th, 2014) in [-5, 5]. Because bonds are thinly traded, bond CARs are only reported in a wide event window. Distressed firms are those in the top default probability quintile in November 2014. The rest of the firms are non-distressed. Panel B shows univariate tests of bond CARs around the 2017 EMC ruling (January 17th, 2017) in [-5, 5]. Distressed firms are those in the top default probability quintile in December 2016. The rest of the firms are non-distressed. *, **, *** Statistical significance in two-tailed t-tests at the 10%, 5%, 1% levels, respectively.

Table 2.4 Firm characteristics

	Investment	Asset growth	R&D	ROA volatility	Equity volatility	Leverage	Ln(Market value of equity)	Ln(Sale)	Depreciation	Tobin's q	Quarter stock return	Default probability
Panel A: Total												
Mean	0.013	0.021	0.012	0.025	0.054	0.292	7.041	5.354	0.011	2.070	0.029	
Median	0.008	0.005	0.000	0.010	0.043	0.270	7.121	5.540	0.009	1.609	0.022	
SD	0.015	0.132	0.030	0.042	0.043	0.217	2.069	2.198	0.008	1.448	0.205	
N	39,680	39,867	40,133	37,893	40,148	38,989	39,893	39,085	39,425	39,828	39,838	
Panel B: The 2014 EMC ruling												
Treat (2014)												
Mean	0.014	0.013	0.004	0.015	0.044	0.364	8.656	7.063	0.011	1.819	0.034	0.033
N	9,209	9,220	8, 959	9,058	9,245	9,010	9,221	9,192	9,137	9,204	9,213	9,249
Control (2014)												
Mean	0.012	0.023	0.016	0.029	0.060	0.258	6.355	4.611	0.011	2.174	0.026	0.050
N	23,565	23,633	23,309	21,795	23,863	23,222	23,635	22,975	23,334	23,605	23,587	23,889
Panel C: The 2017 EMC ruling												
Treat (2017)												
Mean	0.013	0.015	0.005	0.018	0.045	0.391	8.699	7.025	0.011	1.896	0.018	0.061
N	7,829	8,482	9,877	8,380	8,605	8,340	8,511	8,485	8,425	8,484	7,901	8,610
Control (2017)												
Mean	0.011	0.022	0.020	0.032	0.063	0.278	6.308	4.556	0.011	2.215	0.012	0.090
N	18,354	20,191	24,427	18,918	20,890	20,141	20,249	19,433	19,929	20,187	18,774	20,909

Panel A shows summary statistics of the full sample from 2013 to 2018. Investment is Capex in quarter t scaled by Total assets in quarter t-1. Asset growth is the growth in total assets from t-1 to t. R&D is calculated as Xrd/At. Missing R&D is set to zero. ROA volatility is the standard deviation of ROA in the previous eight quarters. Equity volatility is the standard deviation of weekly return in quarter t. Leverage is defined as (Dltt+Dlc)/At. Ln(Market value of equity) is the natural logarithm of the number of shares outstanding times end of year share price. Depreciation is scaled by total assets. Tobin's q is (At+Prcc*Csho-Ceq)/At. I winsorize all continuous variables at the 1% and 99% levels. Panel B shows summary statistics of treated and control groups around the 2014 EMC ruling. The treated group includes firms with outstanding bonds with an offering amount of $10 million or above (with offering date before November 30th, 2014 and maturity date after December 31st, 2016). Default probability is calculated using the Merton distance-to-default model in November 2014. Panel C shows summary statistics of treated and control groups around the 2017 EMC ruling. The treated group includes firms with outstanding bonds with an offering amount of $10 million or above (with offering date before December 31st, 2016 and maturity date after December 31st, 2018). Default probability is calculated using the Merton distance-to-default model in December 2016

Table 2.5 Investment: difference-in-difference-in-differences results around the 2014 Education Management Corporation ruling

	Predicted sign of parameter estimate	(1) Investment	(2) Asset growth	(3) R&D
$Treat_i \times Post\text{-}2014_t \times Distress_i$	-	-0.004***	-0.024**	-0.001*
		(0.001)	(0.011)	(0.001)
$Treat_i \times Post\text{-}2014_t$		-0.000***	-0.012***	-0.000
		(0.000)	(0.003)	(0.000)
$Post\text{-}2014_t \times Distress_i$		-0.000	-0.020**	0.000
		(0.000)	(0.008)	(0.000)
$ROA_{i,t-1}$		0.006**	-0.056	-0.028***
		(0.002)	(0.036)	(0.005)
$Size_{i,t-1}$		-0.007***	-0.170***	-0.007***
		(0.001)	(0.019)	(0.001)
Market value of $equity_{i,t-1}$		0.006***	0.043***	0.001**
		(0.000)	(0.005)	(0.000)
$Leverage_{i,t-1}$		-0.004***	-0.050***	0.001
		(0.001)	(0.016)	(0.001)
$Ln(Sale)_{i,t-1}$		0.002***	0.007	0.001**
		(0.000)	(0.006)	(0.001)
$Depreciation_{i,t-1}$		-0.099***	0.886**	0.011
		(0.038)	(0.416)	(0.045)
Tobin's $q_{i,t-1}$		-0.000	0.023***	-0.000
		(0.000)	(0.003)	(0.000)
Two-quarter stock price $change_{i,t-1}$		-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)
Constant		0.012***	0.834***	0.046***
		(0.004)	(0.109)	(0.005)
Firm FE		Yes	Yes	Yes
Quarter FE		Yes	Yes	Yes
N		28,821	28,884	28,884
Adj. R^2		0.688	0.156	0.878

This table presents OLS estimates of investment regressions. The sample contains firm-quarter observations from Compustat from 2013 to 2016. Dependent variables of the three columns are Capex/lagged At, (At-lagged At)/lagged

At, and Xrd/At. $Treat_i$ is a dummy variable, which equals one if firm i has outstanding public bonds with an offering amount of $10 million or above (with offering date before November 30th, 2014 and maturity date after December 31st, 2016). Post-2014_t is a dummy variable, which equals one after 2014. $Distress_i$ is a dummy variable, which equals one if firm i is in the top default probability quintile in November 2014. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.6 Investment: difference-in-difference-in-differences results around the 2017 Education Management Corporation ruling

	Predicted sign o parameter estimat	(1) Investment	(2) Asset growth	(3) R&D
$Treat_i \times Post\text{-}2016_t \times Distress_i$	+	0.002***	0.002	0.002***
		(0.001)	(0.008)	(0.001)
$Treat_i \times Post\text{-}2016_t$		0.000	-0.010***	0.000
		(0.000)	(0.003)	(0.000)
$Post\text{-}2016_t \times Distress_i$		0.000	-0.022***	-0.003***
		(0.000)	(0.007)	(0.000)
$ROA_{i,t-1}$		0.004**	-0.112***	-0.033***
		(0.002)	(0.040)	(0.004)
$Size_{i,t-1}$		-0.007***	-0.190***	-0.006***
		(0.001)	(0.017)	(0.001)
Market value of $equity_{i,t-1}$		0.004***	0.035***	-0.000
		(0.000)	(0.005)	(0.000)
$Leverage_{i,t-1}$		-0.003***	-0.033*	0.002
		(0.001)	(0.020)	(0.002)
$Ln(Sale)_{i,t-1}$		0.000**	0.008	0.001
		(0.000)	(0.005)	(0.001)
$Depreciation_{i,t-1}$		-0.136***	0.100	0.043
		(0.038)	(0.535)	(0.049)
Tobin's $q_{i,t-1}$		-0.000*	0.027***	0.001***
		(0.000)	(0.003)	(0.000)
Two-quarter stock price $change_{i,t-1}$		-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)
Constant		0.030***	1.020***	0.052***
		(0.002)	(0.109)	(0.005)
Firm FE		Yes	Yes	Yes
Quarter FE		Yes	Yes	Yes
N		28,078	30,055	30,055
Adj. R^2		0.677	0.151	0.869

This table presents OLS estimates of investment regressions. The sample contains firm-quarter observations from Compustat from 2015 to 2018. Dependent variables of the three columns are Capex/lagged At, (At-lagged At)/lagged At, and Xrd/At. $Treat_i$ is a dummy variable, which equals one if firm i has outstanding public bonds with an offering amount of $10 million or above (offering date before December 31st, 2016 and maturity date after December 31st, 2018). $Post\text{-}2016_t$ is a dummy variable, which equals one after 2016. $Distress_i$ is a dummy variable, which equals one if firm i is in the top default probability quintile in December 2016. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.7 Investment efficiency around the 2014 Education Management Corporation ruling

	Investment	
	(1)	(2)
	Investment opportunities$_{i,t-1}$ = Tobin's q$_{i,t-1}$	Investment opportunities$_{i,t-1}$ =Sales growth$_{i,t-1}$
Treat$_i$ × Post-2014$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$	0.003	0.009***
	(0.002)	(0.003)
Treat$_i$ × Post-2014$_t$ × Investment opportunities$_{i,t-1}$	-0.001***	-0.000
	(0.000)	(0.001)
Treat$_i$ × Distress$_i$ × Investment opportunities$_{i,t-1}$	0.010***	0.002
	(0.003)	(0.002)
Post-2014$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$	-0.000	-0.001
	(0.000)	(0.001)
Distress$_i$ × Investment opportunities$_{i,t-1}$	-0.000	0.001
	(0.000)	(0.001)
Treat$_i$ × Investment opportunities$_{i,t-1}$	0.003***	-0.001**
	(0.000)	(0.000)
Post-2014$_t$ × Investment opportunities$_{i,t-1}$	0.000***	0.000
	(0.000)	(0.001)
Treat$_i$ × Post-2014$_t$ × Distress$_i$	-0.009***	-0.006***
	(0.003)	(0.001)
Treat$_i$ × Post-2014$_t$	0.000	-0.000**
	(0.000)	(0.000)
Post-2014$_t$ × Distress$_i$	-0.001	-0.002***
	(0.001)	(0.000)
Investment opportunities$_{i,t-1}$	0.001***	-0.001**
	(0.000)	(0.000)
Size$_{i,t-1}$	0.000	-0.001***
	(0.000)	(0.000)
ROA$_{i,t-1}$	0.012***	0.015***
	(0.002)	(0.003)
Leverage$_{i,t-1}$	-0.010***	-0.009***
	(0.001)	(0.001)
Cash$_{i,t-1}$	-0.005***	-0.004***
	(0.001)	(0.001)
Constant	0.008**	0.027***
	(0.003)	(0.003)

Firm FE	Yes	Yes
Quarter FE	Yes	Yes
N	30,257	29,411
Adj. R^2	0.681	0.677

This table reports the results from regressions of investment on investment opportunities. The sample contains firm-quarter observations from Compustat from 2013 to 2016. The dependent variable for column (1) and (2) is Capex/lagged At. $Treat_i$, $Post\text{-}2014_t$, and $Distress_i$ are the same as in Table 2.5. Column 1 reports estimates when investment opportunities are measured by Tobin'q. Column 2 reports estimates when investment opportunities are measured by sales growth. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.8 Investment efficiency around the 2017 Education Management Corporation ruling

	Investment	
	(1)	(2)
	Investment opportunities$_{i,t-1}$ = Tobin's q$_{i,t-1}$	Investment opportunities$_{i,t-1}$ =Sales growth$_{i,t-1}$
Treat$_i$ × Post-2016$_t$ × Distress$_i$ × Investment opportunities$_{i,t-}$	-0.001**	-0.001
	(0.000)	(0.002)
Treat$_i$ × Post-2016$_t$ × Investment opportunities$_{i,t-1}$	0.000	0.001
	(0.000)	(0.001)
Treat$_i$ × Distress$_i$ × Investment opportunities$_{i,t-1}$	0.003***	0.003*
	(0.001)	(0.002)
Post-2016$_t$ × Distress$_i$ × Investment opportunities$_{i,t-1}$	0.000	-0.000
	(0.000)	(0.001)
Distress$_i$ × Investment opportunities$_{i,t-1}$	0.000	0.000
	(0.000)	(0.000)
Treat$_i$ × Investment opportunities$_{i,t-1}$	-0.000	-0.001**
	(0.000)	(0.001)
Post-2016$_t$ × Investment opportunities$_{i,t-1}$	-0.000	0.001
	(0.000)	(0.000)
Treat$_i$ × Post-2016$_t$ × Distress$_i$	0.004***	0.003***
	(0.001)	(0.001)
Treat$_i$ × Post-2016$_t$	0.000	0.000
	(0.000)	(0.000)
Post-2016$_t$ × Distress$_i$	-0.000	-0.001
	(0.001)	(0.000)
Investment opportunities$_{i,t-1}$	0.001***	-0.000***
	(0.000)	(0.000)
Size$_{i,t-1}$	-0.002***	-0.003***
	(0.000)	(0.000)
ROA$_{i,t-1}$	0.006***	0.007***
	(0.002)	(0.002)
Leverage$_{i,t-1}$	-0.006***	-0.007***
	(0.001)	(0.001)
Cash$_{i,t-1}$	0.001	0.002
	(0.001)	(0.001)
Constant	0.028***	0.038***
	(0.002)	(0.003)

Firm FE	Yes	Yes
Quarter FE	Yes	Yes
N	29,693	28,608
Adj. R^2	0.666	0.667

This table reports the results from regressions of investment on investment opportunities. The sample contains firm-quarter observations from Compustat from 2015 to 2018. Dependent variable for columns (1) and (2) is Capex/lagged At. $Treat_i$, Post-2016_t, and $Distress_i$ are the same as in Table 2.6. Column 1 reports estimates when investment opportunities are measured by Tobin'q. Column 2 reports estimates when investment opportunities are measured by sales growth. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.9 Offering yield: difference-in-differences results around the 2014 and 2017 Education Management Corporation rulings

	Ln(Offering yield+1)		
	(1)		(2)
Above \$10 million$_j$× Post-2014$_t$	0.037	Above \$10 million$_j$× Post-2016$_t$	0.092**
	(0.034)		(0.044)
Above \$10 million$_j$	0.135***	Above \$10 million$_j$	0.002
	(0.031)		(0.045)
Time to maturity$_j$	0.012	Time to maturity$_j$	0.058**
	(0.027)		(0.029)
Ln(Offering amount)$_j$	-0.058***	Ln(Offering amount)$_j$	-0.027**
	(0.015)		(0.012)
Constant	1.537***	Constant	1.424***
	(0.072)		(0.080)
Seniority-type FE	Yes	Seniority-type FE	Yes
Coupon-type FE	Yes	Coupon-type FE	Yes
Firm FE	Yes	Firm FE	Yes
Quarter FE	Yes	Quarter FE	Yes
S&P Rating FE	Yes	S&P Rating FE	Yes
N	5,963	N	4,965
Adj. R^2	0.886	Adj. R^2	0.896

This table reports the results from regressions of offering yield. The sample contains new bond issue observations from 2013 to 2016 for Column 1, and 2015 to 2018 for Column 2. The dependent variable is the natural logarithm of one plus offering yield. Above \$10 million$_j$ is a dummy variable, which equals one if offering amount of j is more than \$10 million. Seniority type includes junior subordinate, senior secured, senior subordinate, senior unsecured, subordinate, and not ranked. Coupon type includes fixed, step-up, variable, or zero. Bond time to maturity is the number of years between issuance and maturity. Bond offering amount is the natural logarithm of the face value at issue. All regressions include quarter, firm, seniority type, coupon type, and S&P rating fixed effects. Standard errors are clustered at the firm level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.10 Bond covenant: difference-in-differences results around the 2014 and 2017 Education Management Corporation rulings

	Ln(Number of covenant+1)		
	(1)		(2)
Above \$10 million$_j$× Post-2014$_t$	-0.130***	Above \$10 million$_j$× Post-2016$_t$	0.189***
	(0.041)		(0.048)
Above \$10 million$_j$	0.025	Above \$10 million$_j$	-0.116***
	(0.021)		(0.034)
Time to maturity$_j$	-0.018*	Time to maturity$_j$	-0.030***
	(0.009)		(0.011)
Ln(Offering amount)$_j$	0.042**	Ln(Offering amount)$_j$	0.052***
	(0.018)		(0.017)
Constant	0.212***	Constant	0.338***
	(0.028)		(0.031)
Seniority-type FE	Yes	Seniority-type FE	Yes
Coupon-type FE	Yes	Coupon-type FE	Yes
Firm FE	Yes	Firm FE	Yes
Quarter FE	Yes	Quarter FE	Yes
S&P Rating FE	Yes	S&P Rating FE	Yes
N	16,338	N	11,299
Adj. R^2	0.675	Adj. R^2	0.656

This table reports the results from regressions of bond covenants. The sample contains bond issue observations from 2013 to 2016 for Column 1, and 2015 to 2018 for Column 2. The dependent variable is the natural logarithm of one plus the number of covenants. Above \$10 million$_j$ is a dummy variable, which equals one if bond offering amount of j is more than \$10 million. Seniority type includes junior subordinate, senior secured, senior subordinate, senior unsecured, subordinate, and not ranked. Coupon type includes fixed, step-up, variable, or zero. Bond time to maturity is the number of years between issuance and maturity. Bond offering amount is the natural logarithm of the face value at issue. All regressions include quarter, firm, seniority type, coupon type, and S&P rating fixed effects. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.11 New debt issuance: difference-in-differences results around the 2014 and 2017 Education Management Corporation rulings

	Ln(Number of new debts issued under the TIA +1)		
	(1)		(2)
$Treat_i \times Post\text{-}2014_t \times Distress_i$	-0.041*	$Treat_i \times Post\text{-}2016_t \times Distress_i$	-0.012
	(0.024)		(0.022)
$Treat_i \times Post\text{-}2014_t$	-0.008	$Treat_i \times Post\text{-}2016_t$	-0.020*
	(0.009)		(0.012)
$Post\text{-}2014_t \times Distress_i$	0.002	$Post\text{-}2016_t \times Distress_i$	-0.004**
	(0.002)		(0.002)
$ROA_{i,t-1}$	-0.016	$ROA_{i,t-1}$	0.022
	(0.027)		(0.018)
$Size_{i,t-1}$	-0.022**	$Size_{i,t-1}$	-0.030***
	(0.010)		(0.007)
Market value of $equity_{i,t-1}$	0.012**	Market value of $equity_{i,t-1}$	0.013***
	(0.005)		(0.004)
$Leverage_{i,t-1}$	-0.057***	$Leverage_{i,t-1}$	-0.065***
	(0.017)		(0.013)
$Ln(Sale)_{i,t-1}$	0.002	$Ln(Sale)_{i,t-1}$	0.003
	(0.004)		(0.003)
$Depreciation_{i,t-1}$	-0.277	$Depreciation_{i,t-1}$	-0.447
	(0.485)		(0.366)
Tobin's $q_{i,t-1}$	-0.001	Tobin's $q_{i,t-1}$	-0.002
	(0.002)		(0.002)
Quarter $return_{i,t-1}$	-0.000	Quarter $return_{i,t-1}$	0.000
	(0.000)		(0.000)
Constant	0.122***	Constant	0.184***
	(0.045)		(0.033)
Firm FE	Yes	Firm FE	Yes
Quarter FE	Yes	Quarter FE	Yes
N	28,885	N	30,068
Adj. R^2	0.170	Adj. R^2	0.169

This table reports the results from regressions of new debt issued under the TIA. The sample contains firm-quarter observations from 2013 to 2016 for Column 1, and 2015 to 2018 for Column 2. The dependent variable is the natural logarithm of one plus the number of new public debt issued by firm i in quarter t with offering amount above $10 million. $Treat_i$, $Post\text{-}2014_t$, $Post\text{-}2016_t$, and $Distress_i$ are the same as in previous tables. All regressions include quarter, firm fixed effects. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.12 Firm value: difference-in-difference-in-differences results around the Education Management Corporation rulings

	Tobin's q		
	(1)		(2)
$Treat_i$ × $Post\text{-}2014_t$ × $Distress_i$	0.250***	$Treat_i$ × $Post\text{-}2016_t$ × $Distress_i$	-0.096**
	(0.056)		(0.044)
$Treat_i$ × $Post\text{-}2014_t$	0.133***	$Treat_i$ × $Post\text{-}2016_t$	-0.024
	(0.021)		(0.021)
$Post\text{-}2014_t$ × $Distress_i$	0.068	$Post\text{-}2016_t$ × $Distress_i$	-0.017
	(0.050)		(0.023)
$ROA_{i,t-1}$	-0.044	$ROA_{i,t-1}$	-0.070
	(0.202)		(0.152)
$Size_{i,t-1}$	-1.278***	$Size_{i,t-1}$	-1.113***
	(0.040)		(0.050)
Market value of $equity_{i,t-1}$	0.777***	Market value of $equity_{i,t-1}$	0.791***
	(0.032)		(0.046)
$Leverage_{i,t-1}$	0.715***	$Leverage_{i,t-1}$	0.614***
	(0.089)		(0.115)
$Ln(Sale)_{i,t-1}$	0.056**	$Ln(Sale)_{i,t-1}$	0.110***
	(0.022)		(0.017)
$Depreciation_{i,t-1}$	-5.388***	$Depreciation_{i,t-1}$	-2.399
	(1.969)		(2.602)
Two-quarter stock price $change_{i,t-1}$	0.005***	Two-quarter stock price $change_{i,t-1}$	0.005***
	(0.001)		(0.000)
Constant	5.053***	Constant	3.591***
	(0.284)		(0.277)
Firm FE	Yes	Firm FE	Yes
Quarter FE	Yes	Quarter FE	Yes
N	28,882	N	30,037
Adj. R^2	0.872	Adj. R^2	0.871

This table presents OLS estimates of firm value regressions. Dependent variable is Tobin's Q. The sample contains firm-quarter observations from 2013 to 2016 for Column 1, and 2015 to 2018 for Column 2. $Treat_i$, $Post\text{-}2014_t$, $Post\text{-}2016_t$, and $Distress_i$ are the same as in previous tables. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.13 Investment, risk, and efficiency: debt specialization

Dependent variable	(1) Investment	(2) Asset growth	(3) R&D		(6) Investment		(7) Investment
Panel A: The 2014 EMC ruling							
$Treat_i \times Post\text{-}2014_t \times Distress_i \times$ Debt $Specialization_i$	0.003	-0.070**	-0.010***	$Treat_i \times Post\text{-}2014_t \times Distress_i \times$ Debt $Specialization_i \times$Tobin's $q_{i,t-1}$	0.020**	$Treat_i \times Post\text{-}2014_t \times Distress_i \times$ Debt $Specialization_i \times$Sales $growth_{i,t-1}$	0.005
	(0.003)	(0.034)	(0.003)		(0.008)		(0.010)
$Treat_i \times Post\text{-}2014_t \times Distress_i$	-0.004***	-0.013	0.001	$Treat_i \times Post\text{-}2014_t \times Distress_i \times$Tobin's $q_{i,t-1}$	-0.006*	$Treat_i \times Post\text{-}2014_t \times Distress_i \times$Sales $growth_{i,t-1}$	0.009*
	(0.001)	(0.018)	(0.001)		(0.003)		(0.005)
Adj. R^2	0.696	0.152	0.881		0.694		0.688
N	17,670	17,704	17,704		18,484		18,022
Panel B: The 2017 EMC ruling							
$Treat_i \times Post\text{-}2016_t \times Distress_i \times$ Debt $Specialization_i$	0.002	-0.014	0.010***	$Treat_i \times Post\text{-}2016_t \times Distress_i \times$ Debt $Specialization_i \times$Tobin's $q_{i,t-1}$	-0.004***	$Treat_i \times Post\text{-}2016_t \times Distress_i \times$ Debt $Specialization_i \times$Sales $growth_{i,t-1}$	-0.002
	(0.002)	(0.036)	(0.002)		(0.001)		(0.004)
$Treat_i \times Post\text{-}2016_t \times Distress_i$	-0.001	0.006	0.003**	$Treat_i \times Post\text{-}2016_t \times Distress_i \times$ Tobin's $q_{i,t-1}$	0.000	$Treat_i \times Post\text{-}2016_t \times Distress_i \times$ Sales $growth_{i,t-1}$	0.001
	(0.001)	(0.015)	(0.001)		(0.001)		(0.003)
Adj. R^2	0.668	0.153	0.864		0.662		0.661

N	19,287	20,596	20,596		20,293	19,668

The table summarizes main test results of level, risk, and efficiency of investment in firms with high and low debt specialization levels. Columns 1 – 3 show levels of investment. Columns 4 – 5 present the changes in volatilities. Columns 6 – 7 tabulate the changes in investment efficiency. Panel A reports test results of the 2014 EMC decision. Treat$_i$, Post-2014$_t$, and Distress$_i$ are the same as in Table 2.5. Panel B shows test results of the 2017 EMC decision. Treat$_i$, Post-2016$_t$, and Distress$_i$ are the same as in Table 2.6. Dependent variables are Capex/lagged At, (At-lagged At)/lagged At, Xrd/At, standard deviation of previous eight quarter ROA, and the standard deviation of weekly stock return. Debt specialization$_i$ equals one if firm i has top 20% Debt HHI in 2014Q4 or 2016Q4. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.14 Firm characteristics of treated and control firms after propensity score matching

	Investment	Asset growth	R&D	ROA volatility	Equity volatility	Leverage	Ln(Market value of equity)	Ln(Sale)	Depreciation	Tobin's q	Quarter stock return	Default probability
Panel A: The 2014 EMC ruling												
Treat (2014)												
Mean	0.013	0.013	0.005	0.016	0.019	0.349	8.712	7.146	0.011	1.917	0.037	0.024
N	6,881	6,890	6,896	6,832	6,895	6,720	6,890	6,863	6,830	6,887	6,884	6,897
Control (2014)												
Mean	0.014	0.017	0.005	0.017	0.017	0.321	8.578	7.050	0.011	1.711	0.082	0.036
N	6,881	6,897	6,897	6,289	6,897	6,593	6,897	6,897	6,865	6,897	6,881	6,897
Panel B: The 2017 EMC ruling												
Treat (2017)												
Mean	0.012	0.014	0.006	0.020	0.022	0.384	8.689	7.063	0.011	1.995	0.022	0.065
N	7,381	7,888	7,902	7,838	7,908	7,701	7,893	7,862	7,826	7,890	7,398	7,908
Control (2017)												
Mean	0.012	-0.006	0.005	0.015	0.022	0.417	8.353	6.650	0.011	1.932	-0.024	0.094
N	5,437	7,908	7,908	7,432	7,908	7,724	7,908	7,876	7,876	7,908	5,437	7,908

Panel A shows summary statistics of treated and matched control groups around the 2014 EMC ruling from 2013 to 2016. The treated group includes firms with outstanding bonds with an offering amount of $10 million or above (with offering date before November 30th, 2014 and maturity date after December 31st, 2016). I use logistic regression based on ROA, leverage, size, Tobin's q, ROA volatility, PPENT, Investment grade, and Rating in 2014Q4 to identify matched control firms. Investment is Capex in quarter t scaled by Total assets in quarter t-1. Asset growth is the growth in total assets from t-1 to t. R&D is calculated as Xrd/At. ROA volatility is the standard deviation of ROA in the previous eight quarters. Equity volatility is the standard deviation of weekly return in quarter t. Leverage is defined as (Dltt+Dlc)/At. Ln(Market value of equity) is the natural logarithm of the number of shares outstanding times end of year share price. Depreciation is scaled by total assets. Tobin's q is (At+Prcc*Csho-Ceq)/At. Investment grade$_{i,t}$ is a dummy variable, which equals one if firm i's has an investment grade rating. Rating$_{i,t}$ equals on if firm i has a S&P long term bond rating. I winsorize all continuous variables at the 1% and 99% levels. Default probability is calculated using the Merton distance-to-default model in November 2014. Panel B shows summary statistics of treated and matched control groups around the 2017 EMC ruling from 2015 to 2018. The treated group includes firms with outstanding bonds with an offering amount of $10 million or above (with offering date before December 31st, 2016 and maturity date after December 31st, 2018). Matched control firms are identified using logistic regression based on ROA, leverage, size, Tobin's q, ROA volatility in 2016Q4. Investment $grade_{i,t}$ and $Rating_{i,t}$ are not included because Compustat S&P Ratings database in WRDS has been discontinued. Default probability is calculated using the Merton distance-to-default model in December 2016.

Table 2.15 Investment, risk, and efficiency: treated and matched control groups

Dependent variable	Investment	Asset growth	R&D		Investment	Investment
	(1)	(2)	(3)		(6)	(7)
Panel A: The 2014 EMC ruling						
Before: Treat - Control	0.004	0.004	0.004*	$Treat_i$ × Post-2014_t × $Distress_i$ × Tobin's $q_{i,t-1}$	-0.002	
	(0.004)	(0.013)	(0.002)		(0.002)	
After: Treat - Control	-0.001	-0.017	0.004*	$Treat_i$ × Post-2014_t × $Distress_i$ × Sales $growth_{i,t-1}$		0.008**
	(0.003)	(0.013)	(0.002)			(0.003)
Diff-in-Diff	-0.005**	-0.021	-0.000			
	(0.003)	(0.015)	(0.002)	Adj. R^2	0.919	0.914
N	3,844	3,871	3,876	N	12,604	12,444
Panel B: The 2017 EMC ruling						
Before: Treat - Control	-0.001	-0.011	0.000	$Treat_i$ × Post-2016_t × $Distress_i$ × Tobin's $q_{i,t-1}$	-0.001**	
	(0.002)	(0.011)	(0.003)		(0.000)	
After: Treat - Control	0.001	-0.010	0.004	$Treat_i$ × Post-2016_t × $Distress_i$ × Sales $growth_{i,t-1}$		-0.001
	(0.002)	(0.014)	(0.003)			(0.002)
Diff-in-Diff	0.002	0.000	0.004			
	(0.002)	(0.014)	(0.002)	Adj. R^2	0.891	0.891
N	4,644	5,035	5,052	N	12,067	12,017

The table summarizes main test results of level, risk, and efficiency of investment using propensity-score matching DID. Dependent variables are Capex/lagged At, (At-lagged At)/lagged At, Xrd/At, standard deviation of previous eight quarter ROA, and the standard deviation of weekly stock return. Matched control firms are identified using logistic regression based on ROA, leverage, size, Tobin's q, ROA volatility, PPENT in 2014Q4 or 2016Q4. Investment grade and Rating are only included in the 2014 logistic regression but not in the 2017 logistic regression because Compustat S&P Ratings database in WRDS has been discontinued. Columns 1 - 5 tabulate the differences-in-differences matching estimator[30]. The sample includes distressed firms in Columns 1 - 5. Columns 6 - 7 report results

30 The coefficients are estimated using Stata package *diff*.

of investment efficiency using the treated and matched control full sample. Panel A reports test results of the 2014 EMC decision. $Treat_i$, $Post\text{-}2014_t$, and $Distress_i$ are the same as in Table 2.5. Panel B shows test results of the 2017 EMC decision. $Treat_i$, $Post\text{-}2016_t$, and $Distress_i$ are the same as in Table 2.6. All regressions include quarter and firm fixed effects. Standard errors are clustered by the interaction of quarter and the firm's state of incorporation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix A.2 Appendix of Chapter 3

Appendix A.2.1 Details of Bankruptcy sales with credit bid

Debtor	Year	Credit bidder	Type of creditor	Credit bid Amount	Asset sold
AmericanWest Bancorporation	2010		DIP lender, stalking horse bidder	$2 million credit bid from DIP financing	Wholly owned subsidiary bank
Blockbuster Inc.	2010	Monarch Alternative Capital, Owl Creek Asset Management, Stonehill Capital Management and Värde Partners	All the holders of the senior secured notes or DIP lenders		Substantially all of the assets
Palm Harbor Homes, Inc.	2010	Cavco Industries	DIP lender and competitor	A cash and credit bid of $85.2 million, credit bid from a debtor-in-possession financing facility of $50 million	Substantially all of Palm Harbor's assets
Real Mex Restaurants, Inc.	2011	Tennenbaum Capital Partners, Z Capital Partners and J.P. Morgan Investment Management	Second lien noteholders	A credit bid of $80 million of outstanding second lien debt, $46 million of cash , and the assumption of $38 million of liabilities.	All assets
Grubb & Ellis Company	2012	BGC Partners Inc.	Loan purchaser	A $30 million credit bid	All assets
LifeCare Holdings, Inc.	2012		Secured lenders	A $320 million credit bid	All assets and cash
Furniture Brands International, Inc	2013	Oaktree Capital Management	$50 million term loan purchased from Sycamore Partners + $140 million DIP		All assets
Global Aviation Holdings Inc. (2013)	2013	Cerberus Business Finance LLC	Lender		
Powerwave Technologies, Inc.	2013	The Gores Group (PE)	DIP lender	A $1.5 million credit bid	IP assets

Dendreon Corporation	2014	Deerfield Management Co, Aristeia Capital, Empyrean Capital Partners, Wolverine Asset Management and Partner Fund Management	Noteholders	An agreement that is similar to credit bid: A $275 million minimum bid requirement as part of a deal with holders of its notes. If it does not receive a bid at that price, the noteholders will convert their debt into equity of the company	
Endeavour International Corporation	2014	Wells Fargo Bank and noteholders		A $398 million credit bid	Equity in the U.K. holding company
Quicksilver Resources Inc.	2015	BlueStone	Second-lien creditor	A $93 million in cash+ a $157 million credit bid	Barnett Shale natural gas assets
RadioShack Corporation	2015	Standard General	DIP lender	A credit bid of $118.91 million+$8.48 million in cash and assumed liabilities	
Standard Register Company	2015	Silver Point	Holders of several liens		
Walter Energy, Inc.	2015	Coal Acquisition LLC		A 1.25 billion credit bid + $5.4 million in cash	All assets

Appendix A.2.2 Figures of Chapter 3

Figure 3.1 Average difference in Leverage between treated and control groups (US companies)

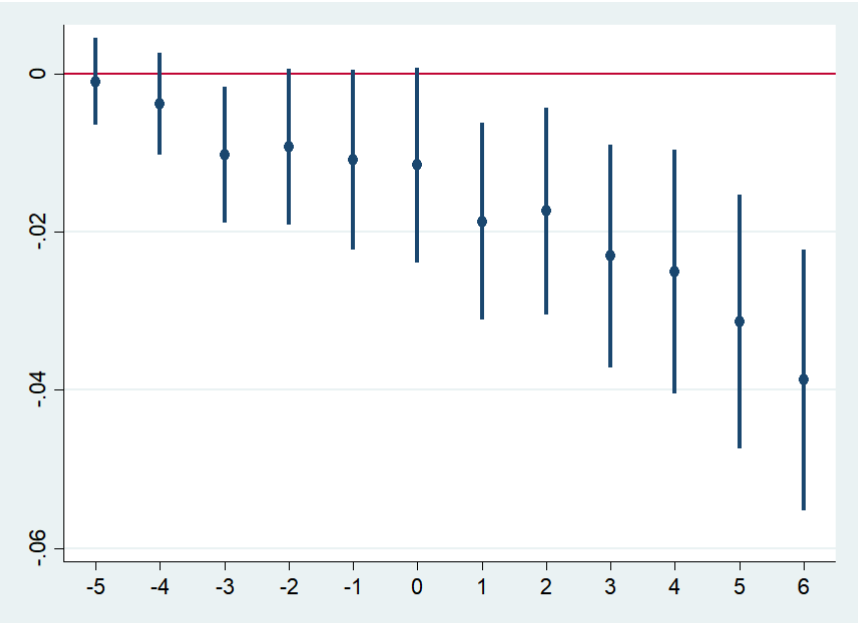


Figure 3.1 presents average difference in Leverage between US firms with high and low default probabilities, conditioning on firm and quarter fixed effects and firm control variables. The event date 0 is 2012Q3. The point estimates and 95% confidence intervals refer to the coefficients of the interaction terms between the $Treat_i$ and quarter dummy variables. The point estimates are relative to the year 2011Q1.

Figure 3.2 Average difference in Leverage between treated and control groups (Foreign companies)

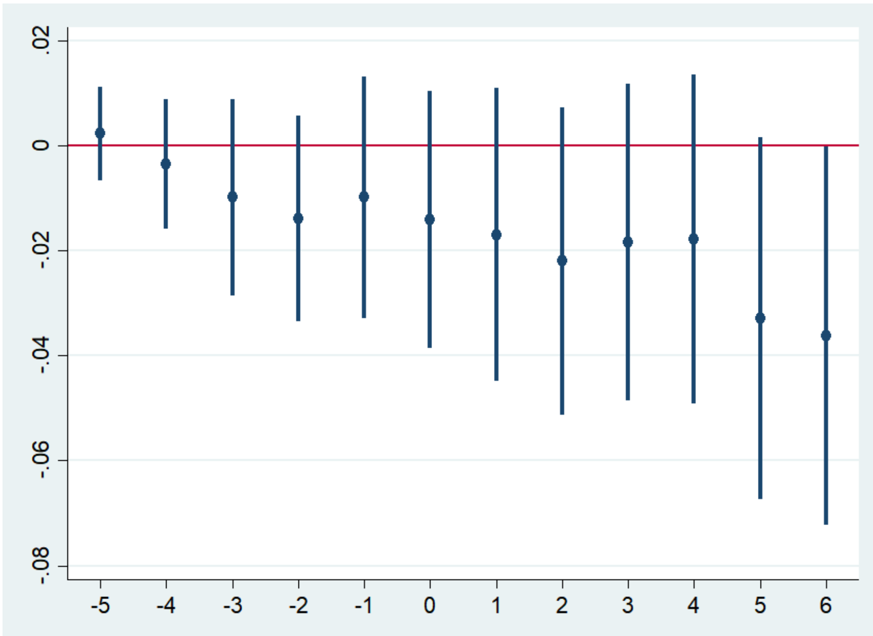


Figure 3.2 presents average difference in Leverage between non-US firms with high and low default probabilities, conditioning on firm and quarter fixed effects and firm control variables. The event date 0 is 2012Q3. The point estimates and 95% confidence intervals refer to the coefficients of the interaction terms between the $Treat_i$ and quarter dummy variables. The point estimates are relative to the year 2011Q1.

Appendix A.2.3 Tables of Chapter 3

Table 3. 1 Summary Statistics

Variable	$Leverage_{i,t}$	$ROA_{i,t-1}$	Stock $return_{i,t-1}$	$Size_{i,t-1}$	$PPENT_{i,t-1}$	Market-to-$book_{i,t-1}$	Hostile takeover $index_{i,t-1}$	(Secured debt/Total $debt)_{i,t}$	(Unsecured debt/Total $debt)_{i,t}$	Net debt $issuance_{i,t}$	Net equity $issuance_{i,t}$	Default probability in January 2010
Panel A: Full sample												
Mean	0.238	-0.004	0.046	6.585	0.262	2.783	0.148	0.422	0.474	0.005	0.004	0.037
SD	0.213	0.059	0.249	2.033	0.237	5.008	0.084	0.442	0.452	0.042	0.046	0.128
N	35,268	36,398	36,395	36,424	36,378	36,402	36,439	25,138	25,138	34,197	33,278	36,467
Panel B: Treat												
Mean	0.337	-0.019	0.059	5.853	0.312	2.209	0.137	0.609	0.326	0.003	0.010	0.132
SD	0.246	0.07	0.319	1.986	0.258	5.999	0.079	0.415	0.392	0.045	0.054	0.213
N	10,076	10,284	10,271	10,291	10,245	10,288	10,306	6,429	6,429	9,664	9,362	10,318
Panel C: Control												
Mean	0.199	0.002	0.041	6.874	0.242	3.009	0.153	0.358	0.524	0.005	0.001	0.000

SD	0.184	0.052	0.214	1.978	0.226	4.539	0.085	0.433	0.460	0.041	0.043	0.000
N	25,192	26,114	26,124	26,133	26,133	26,114	26,133	18,709	18,709	24,533	23,916	26,149

This table provides summary statistics to the firm quarterly financial data from 2010 to 2014. Debt structure characteristics data is from Capital IQ. Firms in the financial industry are excluded. Treated firms are those with top 30% of default probability in January 2010. Control firms are the remained firms. Leverage$_{i,t}$ is (dlttq+dlcq)/atq. ROA$_{i,t-1}$ is lagged net income scaled by lagged total assets (niq/atq). Stock return$_{i,t-1}$ is calculated as (prccq$_{i,t-1}$/ prccq$_{i,t-2}$)-1. Size$_{i,t-1}$ is natural logarithm of atq$_{i,t-1}$. PPENT$_{i,t-1}$ is ppentq/atq in quarter t-1. Market-to-book$_{i,t-1}$ is (prccq×cshoq)/ceqq in quarter t-1. Hostile takeover index$_{i,t-1}$ is from Cain, McKeon, and Solomon (2017). Net debt issuance$_{i,t}$ is (quarterly change of dltisy-quartely change of dltry)/atq. Net equity issuance$_{i,t}$ is (quarterly change of sstky-quartely change of prstkcy)/atq. The default probability in January 2010 is calculated using the Merton distance to default model. All continuous variables are winsorized at the 1% and 99% levels.

Table 3. 2 The frequency of Section 363 sales and credit bidding in bankruptcy

Year	Credit bid	363 sale	Chapter 11	Percentage of 363 sale among Chapter 11	Percentage of credit bid among Chapter 11	Percentage of credit bid among 363 sale
2010	3	6	28	21%	11%	50%
2011	1	3	22	14%	5%	33%
2012	2	7	24	29%	8%	29%
2013	3	6	25	24%	12%	50%
2014	2	6	17	35%	12%	33%
2015	4	7	25	28%	16%	57%

This table shows the percentage of 363 sale and credit bidding in bankruptcy by year. Chapter 11 filings and the usage of 363 sale are obtained from the UCLA-LoPucki Bankruptcy Research Database. The frequency of credit bidding in the auction is hand collected by searching for each bankruptcy filing with 363 sale.

Table 3. 3 Stock CARs around Radlax Gateway Hotel, et al., v. Amalgamated Bank

Panel A: Stock CARs in [-5,5]

Stock CAR [-5,5]	Full sample	Top 50% secured/total debt ratio	Bottom 50% secured/total debt ratio	Difference
Top 50% default probability	-0.007**	-0.009**	-0.003	-0.005
Bottom 50% default probability	0.003	0.009	0.001	0.008
Difference	-0.010***	-0.017**	-0.004	

Panel B: Stock CARs in [-3,3]

Stock CAR [-3,3]	Full sample	Top 50% secured/total debt ratio	Bottom 50% secured/total debt ratio	Difference
Top 50% default probability	-0.002	-0.002	-0.003	0.001
Bottom 50% default probability	0.005	0.017	-0.002	0.019*
Difference	-0.008	-0.018*	-0.001	

Panel C: Stock CARs in [-1,1]

Stock CAR [-1,1]	Full sample	Top 50% secured/total debt ratio	Bottom 50% secured/total debt ratio	Difference
Top 50% default probability	-0.003	-0.002	-0.004	0.001
Bottom 50% default probability	0.004	0.010	0.001	0.009
Difference	-0.007*	-0.013*	-0.005	

Panel D: Stock CARs in [0]

Stock CAR [0]	Full sample	Top 50% secured/total debt ratio	Bottom 50% secured/total debt ratio	Difference

Top 50% default probability	-0.001	-0.000	-0.002	0.002
Bottom 50% default probability	0.005	0.010	0.001	0.009
Difference	-0.005	-0.010	-0.003	

Table 3.3 tabulates stock CAR in [-5,5], [-3,3], [-1,1], and [0] estimated using the Fama-French three-factor model. The event day is May 29th, 2012. Firms are divided into subsamples according to secured debt/total debt ratios in 2010Q1 and default probabilities in January 2010. Firms are divided into subsamples according to secured debt/total debt ratio in 2010Q1 and default probability in January 2010. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.4 Takeover threats from secured creditors and debt offering yields

	Offering yield$_{i,j,t}$			
	(1)	(2)	(3)	(4)
Secured debt$_{i,j,t}$	0.558***	-0.008	-0.028	-0.052
	(0.000)	(0.711)	(0.216)	(0.150)
Secured debt$_{i,j,t}$ × Aft$_t$	-0.166**	-0.077	-0.086	-0.134*
	(0.025)	(0.336)	(0.138)	(0.055)
Secured debt$_{i,j,t}$ × Treat$_i$ × Aft$_t$	0.202*	0.114	0.018	-0.006
	(0.059)	(0.281)	(0.834)	(0.961)
Treat$_i$	0.220***			
	(0.000)			
Secured debt$_{i,j,t}$ × Treat$_i$	-0.126	0.155**	0.150***	0.208**
	(0.402)	(0.037)	(0.006)	(0.046)
Treat$_i$ × Aft$_t$	-0.030	-0.060**	-0.131***	
	(0.427)	(0.016)	(0.001)	
Maturity$_{i,j,t}$	0.017***	0.017***	0.017***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Issue amount$_{i,j,t}$	0.022	0.010	0.013	0.015*
	(0.321)	(0.229)	(0.170)	(0.088)
Seniority$_{i,j,t}$	-0.053	-0.138	-0.222	-0.194
	(0.607)	(0.276)	(0.198)	(0.330)
Rating$_{i,j,t}$	-0.012***	0.017***	0.019***	0.020***

	(0.000)	(0.000)	(0.000)	(0.000)
$Covenant_{i,j,t}$	-0.003	-0.000	-0.002	-0.010**
	(0.198)	(0.975)	(0.351)	(0.036)
Constant	1.456***	1.492***	1.550***	1.488***
	(0.000)	(0.000)	(0.000)	(0.000)
Year_quarter FE	Yes	Yes	Yes	No
Firm FE	No	Yes	No	No
Firm × Year FE	No	No	Yes	No
Firm × Year_quarter FE	No	No	No	Yes
N	2,749	2,657	2,253	1,990
Adj. R^2	0.215	0.845	0.891	0.910

I estimate OLS regressions to examine the relation between secured creditor takeover threats and offering yields. The dependent variable is natural logarithm of offering yield of new issued debt j by firm i in quarter t. Secured $debt_{i,j,t}$ takes value of one if debt j is secured. $Treat_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft_t is a dummy variable, which equals one after 2012Q2. $Seniority_{j,t}$ is takes value of one if debt j is senior. $Rating_{i,j,t}$ is a proxy from 0 to 20. $Rating_{i,j,t}$ equals zero if bond j is "not rated" and equals 20 if bond j is "AAA". $Covenant_{j,t}$ is the number of protective covenants of debt j. I control for industry (Fama-French 17 industries) and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 5 Takeover threats from loan-to-own investments and leverage

	Leverage$_{i,t}$		
	(1)	(2)	(3)
Treat$_i$×Aft$_t$	-0.032***	-0.017*	-0.043***
	(0.000)	(0.097)	(0.000)
Treat$_i$×Aft$_t$×Secure$_i$		-0.033**	
		(0.013)	
Treat$_i$×Aft$_t$×Takeover$_i$			0.020*
			(0.088)
Aft$_t$×Secure$_i$		-0.000	
		(0.966)	
Aft$_t$×Takeover$_i$			-0.005
			(0.314)
ROA$_{i,t-1}$	-0.250***	-0.240***	-0.252***
	(0.000)	(0.000)	(0.000)
Stock return$_{i,t-1}$	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)
Size$_{i,t-1}$	0.035***	0.040***	0.034***
	(0.000)	(0.000)	(0.000)
PPENT$_{i,t-1}$	0.175***	0.165***	0.172***
	(0.000)	(0.000)	(0.000)
Market-to-book$_{i,t-1}$	-0.001**	-0.000	-0.001**

	(0.038)	(0.227)	(0.018)
Hostile takeover index$_{i,t-1}$	-0.083	-0.017	-0.080
	(0.620)	(0.912)	(0.626)
Constant	-0.023	-0.077	-0.013
	(0.710)	(0.209)	(0.835)
Firm FE	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes
N	35,084	24,177	35,032
Adj. R^2	0.872	0.887	0.872

I estimate OLS regressions to examine how did US firms adjust leverage when loan-to-own takeover threats increased. The dependent variable is leverage of firm i at the end of quarter t. Treat$_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft$_t$ is a dummy variable, which equals one after 2012Q2. Secure$_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. Takeover$_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3.6 Takeover threats from loan-to-own investments and secured debt ratio

	(1) (Secured debt/Total debt)$_{i,t}$	(2) (Unsecured debt/Total debt)$_{i,t}$	(3) (Secured debt/Total debt)$_{i,t}$	(4) (Unsecured debt/Total debt)$_{i,t}$	(5) (Secured debt/Total debt)$_{i,t}$	(6) (Unsecured debt/Total debt)$_{i,t}$
$Treat_i \times Aft_t$	0.008	-0.008	0.047**	-0.048**	0.081***	-0.082***
	(0.572)	(0.570)	(0.045)	(0.039)	(0.003)	(0.003)
$Treat_i \times Aft_t \times Takeover_i$			-0.067**	0.069**		
			(0.024)	(0.020)		
$Treat_i \times Aft_t \times Secure_i$					-0.052	0.054
					(0.115)	(0.104)
$Aft_t \times Takeover_i$			0.043***	-0.044***		
			(0.003)	(0.003)		
$Aft_t \times Secure_i$					-0.108***	0.108***
					(0.000)	(0.000)
$Leverage_{i,t-1}$	-0.033	0.037	-0.033	0.037	-0.039	0.043
	(0.542)	(0.494)	(0.543)	(0.495)	(0.453)	(0.407)
$ROA_{i,t-1}$	-0.003	0.001	-0.009	0.007	-0.016	0.013
	(0.962)	(0.991)	(0.899)	(0.926)	(0.818)	(0.847)
Stock return$_{i,t-1}$	0.009	-0.009	0.009	-0.009	0.009	-0.009
	(0.171)	(0.185)	(0.173)	(0.187)	(0.187)	(0.202)
$Size_{i,t-1}$	-0.048**	0.048**	-0.046**	0.046**	-0.044**	0.044**
	(0.027)	(0.027)	(0.034)	(0.034)	(0.034)	(0.034)
$PPENT_{i,t-1}$	0.052	-0.050	0.064	-0.063	0.063	-0.061
	(0.585)	(0.593)	(0.499)	(0.503)	(0.486)	(0.494)
Market-to-book$_{i,t-1}$	0.000	-0.000	0.000	-0.000	0.000	-0.000

	(0.514)	(0.553)	(0.566)	(0.609)	(0.782)	(0.833)
Hostile takeover index$_{i,t-1}$	-0.590	0.587	-0.758*	0.759*	-0.905*	0.887*
	(0.215)	(0.210)	(0.084)	(0.079)	(0.051)	(0.053)
Constant	0.897***	0.102	0.894***	0.104	0.938***	0.062
	(0.000)	(0.567)	(0.000)	(0.555)	(0.000)	(0.717)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20,083	20,083	20,083	20,083	19,982	19,982
Adj. R^2	0.846	0.846	0.847	0.846	0.851	0.850

I estimate OLS regressions to examine how do firms adjust secured debt ratios when takeover threats from secured creditors increased. The dependent variable is secured debt ratio and unsecured debt ratio. Treat$_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft$_t$ is a dummy variable, which equals one after 2012Q2. Secure$_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. Takeover$_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 7 Takeover threats from loan-to-own investments and secured debt issuance

	Secured $debt_{i,j,t}$
$Treat_i \times Aft_t$	-0.768**
	(0.018)
$Treat_i$	0.564**
	(0.030)
$Size_{i,t}$	-0.384***
	(0.000)
$ROA_{i,t}$	-10.434***
	(0.000)
$Leverage_{i,t}$	1.589***
	(0.006)
$Ln(Maturity+1)_{i,j,t}$	-1.821***
	(0.000)
Bond issure $amount_{i,j,t}$	0.365*
	(0.089)
Offering $yield_{i,j,t}$	2.537***
	(0.000)
$Rating_{i,j,t}$	0.074***
	(0.006)
Number of issues by the same $firm_i$	0.005*
	(0.062)
Hostile takeover $index_{i,t-1}$	0.215
	(0.846)
Constant	-2.808*
	(0.062)
Industry FE	Yes

Year_quarter FE	Yes
N	2,141
Pseudo R^2	0.478

The table presents the results of Probit regression of how loan-to-own takeover threats influence the probability of issuing secured debt. The dependent variable Secured debt$_{i,j,t}$ is a dummy variable, which equals one if the newly issued debt j by firm i is secured, and zero if it is unsecured. Treat$_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft$_t$ is a dummy variable, which equals one after 2012Q2. Rating$_{i,j,t}$ is a proxy from 0 to 20. Rating$_{i,j,t}$ equals zero if bond j is “not rated” and equals 20 if bond j is “AAA”. I control for industry (Fama French 17 industries) and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 8 Takeover threats from loan-to-own investments and net debt issuance

	Net Debt Issuance$_{i,t}$		
	(1)	(2)	(3)
Treat$_i$×Aft$_t$	-0.002	-0.000	-0.005**
	(0.148)	(0.955)	(0.013)
Treat$_i$×Aft$_t$×Secure$_i$		-0.004	
		(0.276)	
Treat$_i$×Aft$_t$×Takeover$_i$			0.005**
			(0.046)
Aft$_t$×Takeover$_i$			-0.002*
			(0.094)
Aft$_t$×Secure$_i$		0.001	
		(0.400)	
Leverage$_{i,t-1}$	-0.096***	-0.110***	-0.098***
	(0.000)	(0.000)	(0.000)
ROA$_{i,t-1}$	-0.009	-0.015	-0.010
	(0.323)	(0.233)	(0.274)
Stock return$_{i,t-1}$	-0.002*	-0.002	-0.002*
	(0.070)	(0.117)	(0.066)
Size$_{i,t-1}$	-0.010***	-0.007***	-0.010***
	(0.000)	(0.000)	(0.000)
PPENT$_{i,t-1}$	0.062***	0.056***	0.061***
	(0.000)	(0.000)	(0.000)
Market-to-book$_{i,t-1}$	-0.000	0.000	-0.000
	(0.669)	(0.386)	(0.496)
Hostile takeover index$_{i,t}$	0.002	0.038	0.008

	(0.968)	(0.628)	(0.899)
Constant	0.075***	0.056***	0.077***
	(0.000)	(0.002)	(0.000)
Firm FE	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes
N	32,977	22,790	32,935
Adj. R^2	0.059	0.054	0.060

I estimate OLS regressions to examine whether firms reduced leverage by reducing net debt issuance when loan-to-own threat increased. The dependent variable is (quarterly change of dltisy-quartely change of dltry)/atq. $Treat_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft_t is a dummy variable, which equals one after 2012Q2. $Secure_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. $Takeover_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 9 Takeover threats from loan-to-own investments and net equity issuance

	Net Equity Issuance$_{i,t}$		
	(1)	(2)	(3)
Treat$_i$×Aft$_t$	-0.001	-0.002	-0.001
	(0.285)	(0.414)	(0.607)
Treat$_i$×Aft$_t$×Secure$_i$		0.002	
		(0.545)	
Treat$_i$×Aft$_t$×Takeover$_i$			-0.001
			(0.801)
Aft$_t$×Secure$_i$		0.002*	
		(0.082)	
Aft$_t$×Takeover$_i$			-0.002
			(0.189)
Leverage$_{i,t-1}$	0.038***	0.046***	0.038***
	(0.000)	(0.000)	(0.000)
ROA$_{i,t-1}$	-0.083***	-0.094***	-0.082***
	(0.000)	(0.000)	(0.000)
Stock return$_{i,t-1}$	0.013***	0.013***	0.012***
	(0.000)	(0.000)	(0.000)
Size$_{i,t-1}$	-0.029***	-0.028***	-0.029***
	(0.000)	(0.000)	(0.000)
PPENT$_{i,t-1}$	0.031***	0.023	0.032***
	(0.004)	(0.106)	(0.003)
Market-to-book$_{i,t-1}$	0.000	0.000	0.000
	(0.397)	(0.714)	(0.291)
Hostile takeover index$_{i,t}$	0.080	0.135	0.094

	(0.406)	(0.190)	(0.329)
Constant	0.164***	0.150***	0.161***
	(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes
N	32,029	22,047	31,977
Adj. R^2	0.295	0.300	0.292

I estimate OLS regressions to examine whether firms reduced leverage by reducing net debt issuance when loan-to-own threats increased. The dependent variable is (quarterly change of sstky-quartely change of prstkcy)/atq. $Treat_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft_t is a dummy variable, which equals one after 2012Q2. $Secure_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. $Takeover_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3.10 Takeover threats from loan-to-own investments and CEO incentives

	$Leverage_{i,t}$
$Treat_i \times Aft_t \times Delta_{i,t-1}$	-0.025*
	(0.014)
$Treat_i \times Aft_t$	0.000
	(0.010)
$Delta_{i,t-1}$	-0.013**
	(0.005)
$Treat_i \times Delta_{i,t-1}$	-0.020
	(0.019)
$Aft_t \times Delta_{i,t-1}$	0.008
	(0.005)
$ROA_{i,t-1}$	-0.317***
	(0.048)
Stock $return_{i,t-1}$	0.002
	(0.004)
$Size_{i,t-1}$	0.056***
	(0.011)
$PPENT_{i,t-1}$	0.107*
	(0.062)
Market-to-$book_{i,t-1}$	-0.001
	(0.000)
Hostile takeover $index_{i,t-1}$	-0.536**
	(0.233)
Constant	-0.114
	(0.095)

Firm FE	Yes
Year_quarter FE	Yes
N	18,138
Adj. R^2	0.892

I estimate OLS regressions to examine the relation among leverage, loan-to-own takeover threats, and CEO incentives. The dependent variable is leverage. $Treat_i$ is a dummy variable, whch equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft_t is a dummy variable, which equals one after 2012Q2. $Delta_{i,t-1}$ is CEO pay-performance sensitivity, i.e., dollar change in CEO wealth associated with a 1% change in the firm's stock price (in $000s) in quarter t-1. CEO delta is obtained from Core and Guay (2002) and Coles, Daniel, and Naveen (2006). I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 11 Takeover threats from loan-to-own investments and leverage (foreign companies)

	$Leverage_{i,t}$	
	(1)	(2)
$Treat_i \times Aft_t$	-0.040	-0.055
	(0.150)	(0.225)
$Treat_i \times Aft_t \times Secure_i$		0.032
		(0.549)
$Aft_t \times Secure_i$		-0.008
		(0.604)
$ROA_{i,t-1}$	-0.588***	-0.586***
	(0.008)	(0.006)
Stock $return_{i,t-1}$	-0.007	-0.007
	(0.584)	(0.577)
$Size_{i,t-1}$	0.054**	0.052**
	(0.015)	(0.024)
$PPENT_{i,t-1}$	0.068	0.066
	(0.301)	(0.308)
$Market\text{-}to\text{-}book_{i,t-1}$	0.002	0.002
	(0.519)	(0.511)
Constant	-0.177	-0.163
	(0.303)	(0.371)
Firm FE	Yes	Yes

Year_quarter FE	Yes	Yes
N	3,050	3,050
Adj. R^2	0.862	0.862

I estimate OLS regressions to examine how did foreign firms adjust leverage when loan-to-own takeover threats increased. The dependent variable is leverage. $Treat_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero otherwise. Aft_t is a dummy variable, which equals one after 2012Q2. $Secure_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. $Takeover_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 12 Summary Statistics: treated and matched control groups

Variable	$Leverage_{i,t}$	$ROA_{i,t-1}$	Stock $return_{i,t-1}$	$Size_{i,t-1}$	$PPENT_{i,t-1}$	Market-to-$book_{i,t-1}$	Hostile takeover $index_{i,t-1}$	(Secured debt/Total $debt)_{i,t}$	(Unsecured debt/Total $debt)_{i,t}$	Net debt $issuance_{i,t}$	Net equity $issuance_{i,t}$	Default probability in January 2010
Panel A: Full sample												
Mean	0.301	-0.014	0.051	5.93	0.304	2.553	0.136	0.559	0.352	0.005	0.009	0.063
SD	0.238	0.067	0.282	1.955	0.261	5.905	0.078	0.435	0.415	0.046	0.054	0.161
N	18,445	18,578	18,578	18,594	18,594	18,583	18,608	12,639	12,639	17,548	16,973	18,624
Panel B: Treat												
Mean	0.338	-0.018	0.062	5.894	0.315	2.254	0.138	0.614	0.321	0.003	0.011	0.125
SD	0.245	0.068	0.315	1.991	0.257	6.083	0.080	0.415	0.391	0.044	0.055	0.210
N	9,235	9,287	9,282	9,293	9,293	9,291	9,300	6,165	6,165	8,726	8,463	9,312
Panel C: Matched control												
Mean	0.263	-0.010	0.040	5.966	0.293	2.852	0.135	0.507	0.382	0.007	0.007	0.000
SD	0.226	0.066	0.245	1.918	0.264	5.707	0.076	0.447	0.435	0.047	0.053	0.000
N	9,210	9,291	9,296	9,301	9,301	9,292	9,308	6,474	6,474	8,822	8,510	9,312

This table provides summary statistics to the firm quarterly financial data from 2010 to 2014. Debt structure characteristics data is from Capital IQ. Firms in the financial industry are excluded. Treated firms are those with top 30% of default probability in January 2010. To identify matched control firms, I conduct one-to-one matching without replacement using the logistic regression according to leverage, size, ROA, Market-to-book, and PPENT in 2012Q2. $Leverage_{i,t}$ is (dlttq+dlcq)/atq. $ROA_{i,t-1}$ is lagged net income scaled by lagged total assets (niq/atq). Stock $return_{i,t-1}$ is calculated as ($prccq_{i,t-1}$/ $prccq_{i,t-2}$)-1. $Size_{i,t-1}$ is natural logarithm of $atq_{i,t-1}$. $PPENT_{i,t-1}$ is ppentq/atq in quarter t-1. Market-to-$book_{i,t-1}$ is (prccq*cshoq)/ceqq in quarter t-1. Hostile takeover $index_{i,t-1}$ is from Cain, McKeon, and Solomon (2017). Net debt $issuance_{i,t}$ is (quarterly change of dltisy-quartely change of dltry)/atq. Net equity $issuance_{i,t}$ is (quarterly change of sstky-quartely change of prstkcy)/atq. The default probability in January 2010 is calculated using the Merton distance to default model. All continuous variables are winsorized at the 1% and 99% levels.

Table 3. 13 Takeover threats from loan-to-own investments and leverage: treated and matched control groups

	Leverage$_{i,t}$		
	(1)	(2)	(3)
Treat$_i$×Aft$_t$	-0.046***	-0.030**	-0.058***
	(0.000)	(0.017)	(0.000)
Treat$_i$×Aft$_t$×Secure$_i$		-0.028*	
		(0.083)	
Treat$_i$×Aft$_t$×Takeover$_i$			0.025*
			(0.075)
Aft$_t$×Secure$_i$		-0.006	
		(0.554)	
Aft$_t$×Takeover$_i$			-0.010
			(0.257)
ROA$_{i,t-1}$	-0.260***	-0.226***	-0.264***
	(0.000)	(0.000)	(0.000)
Stock return$_{i,t-1}$	-0.010***	-0.011***	-0.010***
	(0.001)	(0.002)	(0.001)
Size$_{i,t-1}$	0.029***	0.031***	0.027***
	(0.005)	(0.006)	(0.007)
PPENT$_{i,t-1}$	0.178***	0.178***	0.174***
	(0.001)	(0.001)	(0.001)

Market-to-book$_{i,t-1}$	-0.001**	-0.000	-0.001***
	(0.012)	(0.104)	(0.004)
Hostile takeover index$_{i,t-1}$	-0.072	-0.050	-0.090
	(0.734)	(0.762)	(0.660)
Constant	0.097	0.071	0.114
	(0.212)	(0.353)	(0.133)
Firm FE	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes
N	18,350	12,407	18,334
Adj. R^2	0.864	0.888	0.866

I estimate OLS regressions to examine how did US firms adjust leverage when loan-to-own takeover threats increased. The dependent variable is leverage of firm i at the end of quarter t. Treat$_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero if firm i is a matched control firm. To identify matched control firms, I conduct one-to-one matching without replacement using the logistic regression according to leverage, size, ROA, Market-to-book, and PPENT in 2012Q2. Aft$_t$ is a dummy variable, which equals one after 2012Q2. Secure$_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. Takeover$_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Table 3. 14 Takeover threats from loan-to-own investments and secured debt ratio: treated and matched control groups

	(1) Secured debt/Total debt	(2) Unsecured debt/Total debt	(3) Secured debt/Total debt	(4) Unsecured debt/Total debt	(5) Secured debt/Total debt	(6) Unsecured debt/Total debt
$Treat_i \times Aft_t$	0.019	-0.001	0.057*	-0.031	0.051	-0.042
	(0.351)	(0.964)	(0.065)	(0.211)	(0.125)	(0.204)
$Treat_i \times Aft_t \times Takeover_i$			-0.076*	0.061*		
			(0.063)	(0.078)		
$Treat_i \times Aft_t \times Secure_i$					-0.017	0.039
					(0.686)	(0.319)
$Aft_t \times Takeover_i$			0.061**	-0.044*		
			(0.029)	(0.071)		
$Aft_t \times Secure_i$					-0.157***	0.101***
					(0.000)	(0.000)
$Leverage_{i,t-1}$	0.258***	0.138**	0.259***	0.136**	0.238***	0.162**
	(0.001)	(0.033)	(0.001)	(0.034)	(0.001)	(0.010)
$ROA_{i,t-1}$	0.085	-0.059	0.077	-0.053	0.071	-0.052
	(0.314)	(0.437)	(0.361)	(0.483)	(0.389)	(0.484)
Stock $return_{i,t-1}$	0.016*	-0.009	0.015*	-0.009	0.014	-0.007
	(0.088)	(0.234)	(0.098)	(0.252)	(0.139)	(0.374)
$Size_{i,t-1}$	0.005	0.037	0.005	0.037	0.010	0.034
	(0.855)	(0.141)	(0.835)	(0.142)	(0.696)	(0.161)
$PPENT_{i,t-1}$	0.290**	-0.090	0.295**	-0.094	0.308**	-0.100
	(0.031)	(0.376)	(0.029)	(0.352)	(0.015)	(0.302)

Market-to-book$_{i,t-1}$	0.001	-0.000	0.001	-0.000	0.001	-0.000
	(0.148)	(0.675)	(0.167)	(0.712)	(0.227)	(0.815)
Hostile takeover index$_{i,t-1}$	-0.633	0.588	-0.738	0.641	-0.838*	0.690
	(0.211)	(0.246)	(0.117)	(0.185)	(0.098)	(0.191)
Constant	0.454**	0.035	0.449**	0.041	0.500***	0.005
	(0.020)	(0.847)	(0.021)	(0.819)	(0.008)	(0.979)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,484	12,484	12,484	12,484	12,402	12,402
Adj. R^2	0.715	0.770	0.716	0.770	0.723	0.776

I estimate OLS regressions to examine how do firms adjust secured debt ratios when takeover threats from secured creditors increased. The dependent variable is secured debt ratio and unsecured debt ratio. Treat$_i$ is a dummy variable, which equals one if firm i was in top 30% of default probability in January 2010, and zero if firm i is a matched control firm. To identify matched control firms, I conduct one-to-one matching without replacement using the logistic regression according to leverage, size, ROA, Market-to-book, and PPENT in 2012Q2. Aft$_t$ is a dummy variable, which equals one after 2012Q2. Secure$_i$ is a dummy variable, which equals one if firm i has above median secured debt-to-total debt ratio in 2010Q1. Takeover$_i$ is a dummy variable, which equals one if firm i has above median hostile takeover index in 2009. I control for firm and year-quarter fixed effects. Robust standard errors are clustered at the firm level. *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels.

Appendix A.3 Appendix of Chapter 4

Appendix A.3.1 Promotions of prepaid cards by Toys "R" Us

Date	Promotion
7/15/2017	Groupon: Toys “R” Us $20 eGift Card Only $10
3/12/2017	Groupon: $20 Toys “R” Us eGift Card Only $10
2/7/2017	eBay: $100 Toys “R” Us Gift Card Only $93 shipped
12/6/2016	Groupon: $10 Toys “R” Us eGift Card ONLY $5
10/19/2016	eBay: $50 Toys “R” Us eGift Card – ONLY $40
8/24/2016	Groupon: $20 Toys “R” Us eGift Card Only $10
3/31/2016	eBay: $100 Toys “R” Us Gift Card for $70
3/1/2016	eBay: $100 Toys “R” Us eGift Card for only $85
12/16/2015	eBay: $100 Toys “R” Us Gift Card Only $90
9/24/2015	eBay: $100 Toys “R” Us Gift Card Only $85 Shipped
12/23/2014	Groupon: Free $5 Groupon Bucks with the purchase of a $25.00 Toys “R” Us eGift Card
10/21/2014	eBay: $100 Toys “R” Us Gift Card Only $85 Shipped

The promotions are collected from Hip2Save, Slickdeals, and Clarkdeals. The list provides anecdote evidence that retailers have incentives to offer a deeper discount for prepaid cards when they are close to bankruptcy. I try to capture promotions directly offered by Toys “R” Us, by only including promotions from Groupon and PayPal Official Digital Gift Card on eBay. Price information from exchange platforms is excluded.

Appendix A.3.2 Figures of Chapter 4

Figure 4.1 The supply of capital through prepaid cards

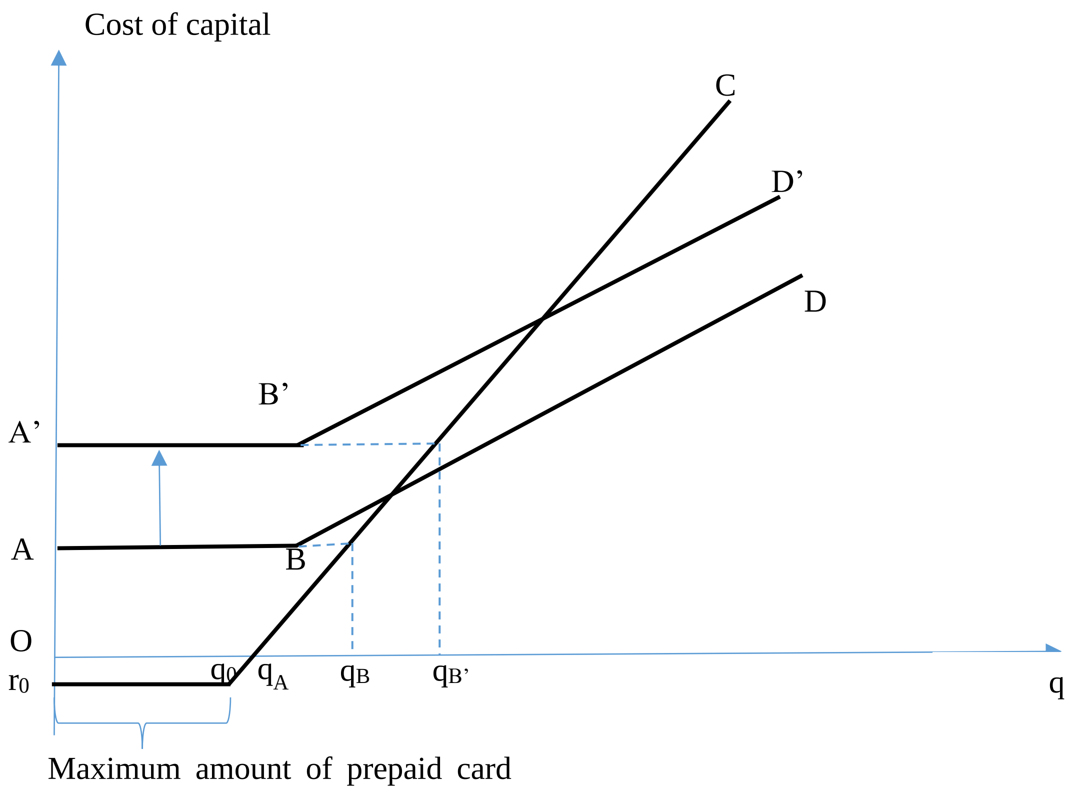
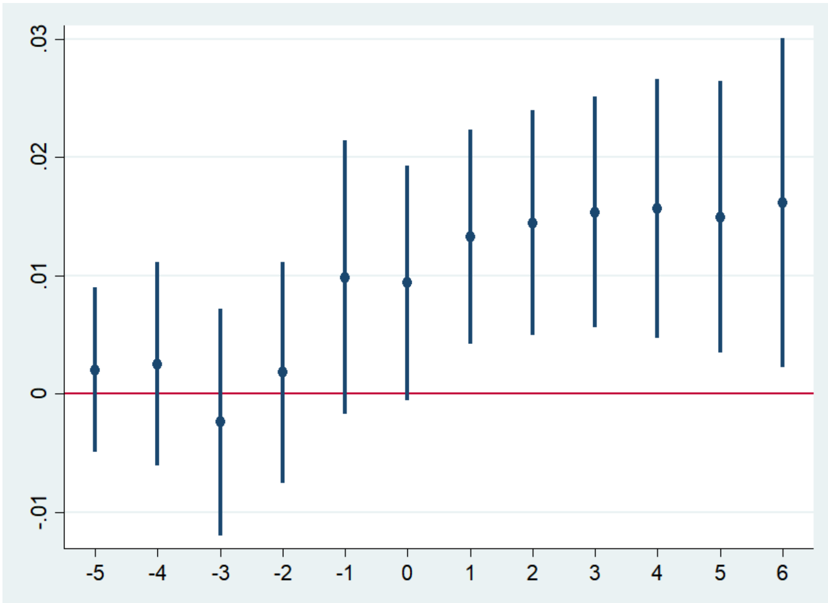
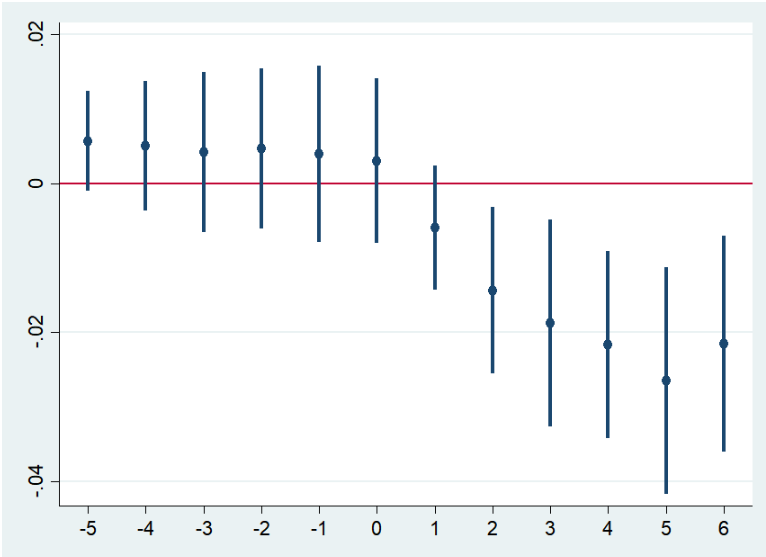


Figure 4.2 Prepaid card balances and interest expense ratios



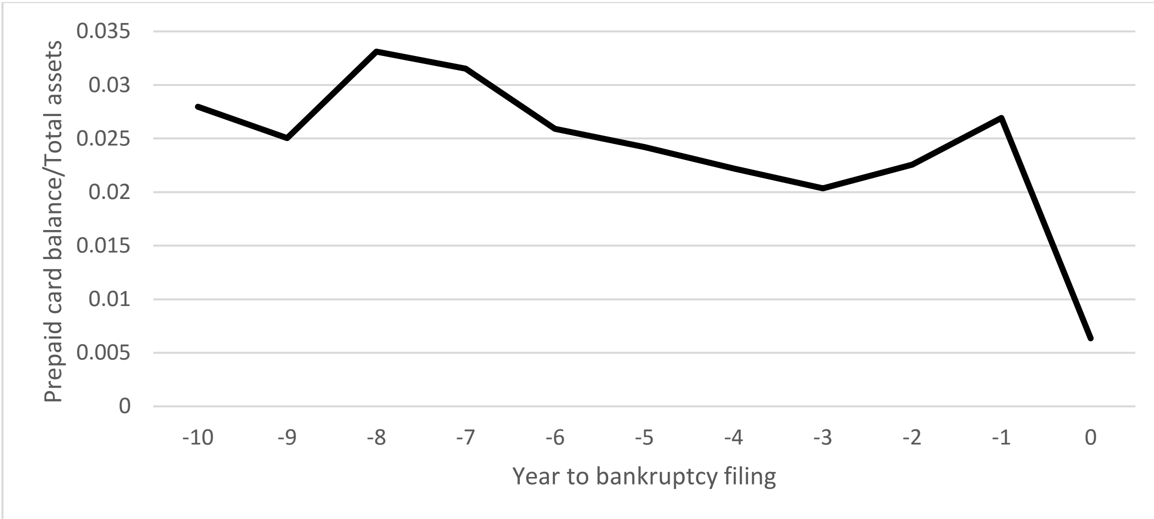
The figure shows coefficients of interactions between year dummy variables and $Interest2009_i$ and 95% confidence intervals of coefficients. $Interest2009_i$ equals one if firm i's average interest expense ratio is above median in 2009, and zero otherwise. The event date 0 is 2010. The sample includes all US retailers from Compustat that report prepaid card balances.

Figure 4.3 Prepaid card balances and market competition



The figure shows coefficients of interactions between year dummy variables and $Compete2009_i$ and 95% confidence intervals of coefficients. $Compete2009_i$ equals one if firm i's HHI is in the bottom 30% in 2009, and zero otherwise. The event date 0 is 2010. The sample includes all US retailers from Compustat that report prepaid card balances.

Figure 4.4 Prepaid card balance/Total assets before bankruptcy filing



The figure maps the average Prepaid card balance/Total assets before bankruptcy filing. t = 0 is the year, in which a firm files for bankruptcy, and the y-axis represents the average Prepaid card balance/Total assets before bankruptcy.

Appendix A.3.3 Tables of Chapter 4

Table 4. 1 Summary statistics

Variable	Mean	St. Dev	Minimum	Median	Maximum	N
Prepaid card balance						
Unredeemed prepaid card balance ($ million)	77.936	154.585	0.108	15.716	970.000	1,511
Unredeemed prepaid card balance$_{i,t}$/Total assets$_{i,t-1}$	0.034	0.038	0.000	0.024	0.263	1,505
Unredeemed prepaid card balance$_{i,t}$/Total liabilities$_{i,t-1}$	0.070	0.072	0.001	0.046	0.401	1,490
Unredeemed prepaid card balance$_{i,t}$/Cash holdings$_{i,t}$	1.001	2.614	0.007	0.233	19.088	1,511
Unredeemed prepaid card balance$_{i,t}$/(Used + unused credit line)$_{i,t}$	0.835	2.317	0.003	0.224	17.876	436
Unredeemed prepaid card balance$_{i,t}$/Accounts payable$_{i,t}$	0.555	1.139	0.002	0.238	8.187	1,511
Breakage income$_{i,t}$/Net income$_{i,t-1}$	0.049	0.328	-1.190	0.019	2.094	573
Breakage income$_{i,t}$/Total assets$_{i,t-1}$	0.004	0.006	0.000	0.002	0.037	573
Firm characteristics						
(Interest expense/Total liabilities)$_{i,t-1}$	0.023	0.021	0.000	0.018	0.106	1,321
HHI$_{i,j,t-1}$	0.201	0.154	0.075	0.147	1.000	1,314
Altman's Z-score$_{i,t-1}$	4.776	3.111	-3.533	4.265	19.077	1,358
Sales$_{i,t-1}$	1.959	0.758	0.338	1.850	5.949	1,468
Size$_{i,t-1}$	6.689	1.620	2.541	6.556	10.893	1,505

$Cash_{i,t-1}$	0.155	0.153	0.002	0.105	0.767	1,468
$Accounts\ payable_{i,t-1}$	0.122	0.094	0.008	0.097	0.555	1,451
$Leverage_{i,t-1}$	0.212	0.251	0.000	0.139	1.435	1,486
$ROA_{i,t-1}$	0.041	0.107	-0.431	0.055	0.286	1,504
$PPENT_{i,t-1}$	0.395	0.202	0.024	0.361	0.881	1,505
$Profit\ margin_{i,t-1}$	0.335	0.125	0.071	0.335	0.725	1,502
$Age_{i,t-1}$	2.715	0.799	0.000	2.773	4.220	1,495

This table presents summary statistics of prepaid card balance and firm characteristics. HHI is the Herfindahl – Hirschman Index for the firm's three-digit SIC industry. Altman Z-score is calculated as 1.2×(Working capital/Total assets) + 1.4× (Retained earnings/Total assets) + 3.3×(EBIT/Total assets) + 0.6 ×(Market value of equity/Total liabilities) + 0.999× (Net sales/Total assets). Sales, Cash, Accounts payable, and PPENT are scaled by lagged Total assets. Firm size is measured as the natural logarithm of Total assets. Leverage is defined as Long-term debt plus Current liabilities divided by Total assets. ROA is Net income divided by Total assets. I calculate Profit margin as (Sales-Cost of goods sold)/Sales. I winsorize all financial variables at the 1^{st} and 99^{th} percentiles.

Table 4.2 Prepaid card balance by year

Year	(1) Prepaid card balance ($ million)	(2) Prepaid card balance/Total assets	(3) Prepaid card balance/Total liabilities	(4) Prepaid card balance/Cash	(5) Prepaid card balance/Line of credit	(6) Prepaid card balance/Accounts payable	(7) Breakage income/Total assets
2004	45.626	0.035	0.086	0.767	1.794	0.357	0.003
2005	53.022	0.036	0.076	0.959	0.431	0.457	0.001
2006	56.570	0.036	0.081	0.909	0.389	0.404	0.004
2007	62.504	0.033	0.075	0.897	0.810	0.411	0.004
2008	57.385	0.030	0.063	1.165	1.045	0.487	0.003
2009	59.199	0.033	0.063	1.117	0.458	0.529	0.004
2010	66.378	0.034	0.070	1.027	1.377	0.511	0.003
2011	72.103	0.034	0.068	0.758	1.300	0.583	0.004
2012	74.962	0.033	0.066	0.661	1.149	0.550	0.004
2013	75.868	0.033	0.066	0.803	0.544	0.542	0.003
2014	89.439	0.034	0.069	0.907	0.967	0.611	0.003
2015	106.630	0.037	0.072	1.290	1.000	0.704	0.003
2016	111.630	0.036	0.064	1.198	0.694	0.706	0.004
2017	110.547	0.038	0.064	1.442	0.991	0.697	0.005
2018	149.155	0.034	0.058	1.272	0.294	0.679	0.003

This table presents summary statistics of prepaid card balance by year. Prepaid card balance and breakage income are hand collected from SEC 10-K filings. The financial data is obtained from Compustat. I winsorize all financial variables at the 1^{st} and 99^{th} percentiles.

Table 4.3 Summary statistics by industry

	(1) Prepaid card balance/Total assets	(2) Breakage income/Total assets	(3) Accounts payable/Total assets	(4) Total credit line/Total assets	(5) Cash/Total assets	(6) Interest expense/Total liabilities	(7) Profit margin
General Merchandise Stores	0.015	0.001	0.129	0.022	0.073	0.032	0.34
Food Stores	0.006	.	0.140	0.073	0.080	0.028	0.303
Automative Dealers & Service Stations	0.011	0.002	0.282	0.020	0.061	0.019	0.426
Apparel & Accessory Stores	0.029	0.003	0.125	0.046	0.219	0.017	0.414
Furniture & Home furnishings Stores	0.039	0.004	0.195	0.035	0.166	0.017	0.37

Eating & Drinking Places	0.044	0.005	0.047	0.121	0.097	0.027	0.227
Miscellaneous Retail	0.044	0.005	0.188	0.073	0.173	0.020	0.380

This table presents data on the prepaid card balance, breakage income, trade credit, credit line, cash holdings, cash, average interest expense, and profit margin. The industry is defined according to two-digit SIC code. I winsorize all financial variables at the 1st and 99th percentiles.

Table 4. 4 Univariate tests on stock CARs

Event window	Full	High (Interest expense/Total liabilities)	Low (Interest expense/Total liabilities)	High-Low	Concentrated	Competitive	Concentrated - Competitive
[-5,5]	0.059	0.155	0.037	0.118	-0.042	0.099	-0.141
[-3,3]	0.033	0.102	0.011	0.091	-0.017	0.053	-0.070
[-1,1]	-0.006	0.022	-0.012	0.034*	0.003	-0.009	0.012
[0]	0.018***	0.034***	0.015*	0.018*	0.034***	0.012	0.022*

Table 4.4 shows univariate tests of stock CARs of retailers around April 30, 2009. All retailers in the sample are split into two groups by (Interest expense/Total liabilities) or HHI index in 2008. Firms with high (low) interest expense ratios are those with above (below) median interest expense ratios in 2008. Firms in a concentrated (competitive) market are those with HHI>0.2 (HHI<0.2) in 2008. Abnormal returns are estimated using the Fama-French three-factor model. Estimation window is [-200, -50]. Differences in CARs between the two groups are reported. *, **, *** Statistical significance in two-tailed t-tests at the 10%, 5%, 1% levels, respectively.

Table 4.5 Prepaid card balances and interest expense ratios

	Unredeemed prepaid card balance$_{i,t}$/Total assets$_{i,t-1}$	
	(1)	(2)
(Interest expense/Total liabilities)$_{i,t-1}$	0.130**	0.065
	(2.16)	(0.88)
Concentrate$_{i,j,t-1}$ × (Interest expense/Total liabilities)$_{i,t-1}$		0.281***
		(2.74)
Altman Z-score$_{i,t-1}$	-0.000	0.000
	(-0.13)	(0.23)
(Sale/Total assets)$_{i,t-1}$	0.015***	0.015***
	(4.10)	(3.88)
Size$_{i,t-1}$	-0.017***	-0.021***
	(-3.36)	(-4.04)
(Cash/Total assets)$_{i,t-1}$	-0.030***	-0.025***
	(-4.06)	(-3.51)
(Accounts payable/Total assets)$_{i,t-1}$	-0.097***	-0.099***
	(-4.00)	(-3.65)
Leverage$_{i,t-1}$	-0.010	-0.013
	(-1.08)	(-1.37)
ROA$_{i,t-1}$	0.003	0.002
	(0.30)	(0.19)
(PPENT/Total assets)$_{i,t-1}$	-0.016	-0.014
	(-0.95)	(-0.69)
Margin$_{i,t-1}$	0.008	0.006
	(0.26)	(0.21)
Age$_{i,t-1}$	0.021**	0.023**
	(2.50)	(2.49)
Cashcycle$_{i,t-1}$	-0.000	-0.000
	(-1.27)	(-0.90)
Concentrate$_{i,j,t-1}$		-0.008**
		(-2.35)
Constant	0.087***	0.110***
	(2.65)	(2.86)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
N	1,119	1,022
Adj. R^2	0.911	0.917

This table presents coefficient estimates from regressions of prepaid card balance to average interest expense. High $margin_{i,t-1}$ is a dummy variable, which equals one if firm i's profit margin in t-1 is above median, and zero otherwise. $Concentrate_{i,j,t-1}$ is a dummy variable, which equals one if HHI>0.2 in t-1, and zero otherwise. Altman Z-score is calculated as 1.2×(Working capital/Total assets) + 1.4× (Retained earnings/Total assets) + 3.3×(EBIT/Total assets) + 0.6 ×(Market value of equity/Total liabilities) + 0.999× (Net sales/Total assets). Sales, Cash, Accounts payable, and PPENT are scaled by lagged Total assets. Firm size is measured as the natural logarithm of Total assets. Leverage is defined as Long-term debt plus Current liabilities divided by Total assets. ROA is Net income divided by Total assets. I calculate Profit margin as (Sales-Cost of goods sold)/Sales. Regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4.6 Prepaid card balances: difference-in-differences results around the CARD Act

	Unredeemed prepaid card balance$_{i,t}$/Total assets$_{i,t-1}$	
	(1)	(2)
Interest2009$_i$ × Aft$_t$	0.011***	
	(3.90)	
Competitive2009$_i$ × Aft$_t$		-0.015***
		(-3.50)
(Interest expense/Total liabilities)$_{i,t-1}$	0.154*	0.098
	(1.95)	(1.34)
Altman Z-score$_{i,t-1}$	-0.000	-0.000
	(-0.35)	(-0.42)
(Sale/Total assets)$_{i,t-1}$	0.020***	0.016***
	(4.54)	(4.02)
Size$_{i,t-1}$	-0.014**	-0.018***
	(-2.45)	(-3.45)
(Cash/Total assets)$_{i,t-1}$	-0.032***	-0.034***
	(-3.68)	(-3.70)
(Accounts payable/Total assets)$_{i,t-1}$	-0.116***	-0.101***
	(-4.10)	(-3.86)
Leverage$_{i,t-1}$	-0.017	-0.013
	(-1.62)	(-1.25)
ROA$_{i,t-1}$	-0.006	-0.004
	(-0.54)	(-0.38)
(PPENT/Total assets)$_{i,t-1}$	-0.020	-0.018
	(-1.12)	(-0.93)
Age$_{i,t-1}$	0.026***	0.025***
	(2.70)	(2.88)
Cashcycle$_{i,t-1}$	-0.000	-0.000
	(-0.97)	(-1.46)
Constant	0.051	0.093***
	(1.33)	(2.66)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
N	850	930
Adj. R^2	0.914	0.911

This table presents OLS estimates of prepaid card balances regressions. The sample contains firm-year observations from Compustat from 2004 to 2018. The dependent variable is (Prepaid card balance/Total assets)$_{i,t}$. Interest2009$_i$ is a dummy variable, which equals one if firm i has above median average interest expense in 2009, and zero otherwise. Compete2009$_i$ is a dummy variable, which equals one if HHI of firm i was in the bottom 30% in 2009. Aft$_t$ is a dummy variable, which equals one starting from 2010, and zero otherwise. Other control variables are the same as in Table

4.5. Standard errors are clustered at the firm level, and all regressions include firm and year fixed effects. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4.7 Prepaid card balance, trade credit, and cash holdings

	Unredeemed prepaid card balance$_{i,t}$/Total assets$_{i,t-1}$	
	(1)	(2)
Payable2009$_i$×Aft$_t$	-0.015***	
	(-4.89)	
Cash2009$_i$×Aft$_t$		-0.008**
		(-2.46)
(Interest expense/Total liabilities)$_{i,t-1}$	0.140**	0.161**
	(2.41)	(2.43)
Altman Z-score$_{i,t-1}$	0.000	-0.000
	(0.44)	(-0.22)
(Sale/Total assets)$_{i,t-1}$	0.013***	0.015***
	(4.27)	(4.08)
Size$_{i,t-1}$	-0.017***	-0.016***
	(-3.55)	(-3.02)
(Cash/Total assets)$_{i,t-1}$	-0.028***	-0.029***
	(-4.38)	(-3.72)
(Accounts payable/Total assets)$_{i,t-1}$	-0.083***	-0.097***
	(-3.51)	(-3.72)
Leverage$_{i,t-1}$	-0.008	-0.011
	(-0.94)	(-1.15)
ROA$_{i,t-1}$	0.004	0.002
	(0.39)	(0.21)
(PPENT/Total assets)$_{i,t-1}$	-0.005	-0.012
	(-0.33)	(-0.71)
Age$_{i,t-1}$	0.023***	0.023***
	(2.92)	(2.65)
Cashcycle$_{i,t-1}$	-0.000	-0.000
	(-0.98)	(-0.97)
Constant	0.084***	0.076**
	(2.90)	(2.34)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
N	1,110	1,021
Adj. R^2	0.918	0.912

This table presents OLS estimates of prepaid card balances regressions. The sample contains firm-year observations from Compustat from 2004 to 2018. The dependent variable is (Prepaid card balance/Total assets)$_{i,t}$. Payable2009$_i$ is a dummy variable, which equals one if firm i has above median accounts payable in 2009, and zero otherwise. $Cash2009_i$ is a dummy variable, which equals one if firm i has above median cash holdings in 2009, and zero otherwise. Aft_t is a dummy variable, which equals one starting from 2010, and zero otherwise. Other control variables are the same as in Table 4.5. Standard errors are clustered at the firm level, and all regressions include firm and year fixed effects. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4. 8 Small business loan amounts around the CARD Act: retailer vs non-retailer

	Ln(New loan amount)$_{j,t}$	
	(1)	(2)
Retail$_j$ × Aft$_t$	-0.017***	-0.051***
	(-3.009)	(-5.106)
Aft$_t$	-0.230***	-0.060***
	(-10.169)	(-2.770)
Retail$_j$ × Aft$_t$ × One year$_j$		-0.482***
		(-12.022)
Retail$_j$ × Aft$_t$ × One-to-five year$_j$		-0.053***
		(-3.614)
Retail$_j$ × Aft$_t$ × Five-to-ten year$_j$		-0.010
		(-0.865)
One year$_j$		1.434***
		(94.628)
Retail$_j$ × One year$_j$		-0.226***
		(-13.517)
Aft$_t$ × One year$_j$		0.235***
		(14.324)
One-to-five year$_j$		-0.352***
		(-42.266)
Retail$_j$ × One-to-five year$_j$		-0.032***
		(-3.463)
Aft$_t$ × One-to-five year$_j$		-0.369***
		(-45.885)
Five-to-ten year$_j$		-0.830***
		(-138.066)
Retail$_j$ × Five-to-ten year$_j$		0.127***
		(15.841)
Aft$_t$ × Five-to-ten year$_j$		-0.083***
		(-12.232)
Ln(Maturity)$_{j,t}$	0.747***	0.920***
	(451.738)	(234.230)
Constant	8.199***	7.889***
	(691.852)	(340.093)
Year FEs	Yes	Yes
County FEs	Yes	Yes
Six-digit NAICS code FEs	Yes	Yes
N	1,215,234	1,215,234

Adj. R^2	0.435	0.435

This table presents OLS estimates results. The sample contains SBA 7(a) data from 2004 to 2018, excluding firms in the Finance and Insurance (Two-digit NAICS=52). The dependent variables are the natural logarithm of loan amount. $Retail_j$ is a dummy variable, which equals one if the borrower of loan j is in the retail industry, and zero otherwise. Aft_t is a dummy variable, which equals one starting from 2010, and zero otherwise. One $year_j$ is a dummy variable, which equals one if the time-to-maturity of loan j is less than one year. One-to-five $year_j$ is a dummy variable, which equals one if the time-to-maturity of loan j is between one and five years. Five-to-ten $year_j$ is a dummy variable, which equals one if the time-to-maturity of loan j is between five and ten years. Standard errors are clustered at the firm level, and all regressions include year, county, and NAICS code fixed effects. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4. 9 Small business loan around the CARD Act: time-to-maturity and interest rate

	$Ln(Maturity)_{j,t}$	$Ln(Interest\ rate)_{j,t}$
	(1)	(2)
$Retail_j \times Aft_t$	0.009***	-0.004**
	(3.31)	(-2.41)
Aft_t	-0.017	0.006**
	(-1.48)	(1.97)
$Ln(Maturity)_{j,t}$		0.024***
		(38.02)
$Ln(New\ loan\ amount)_{j,t}$	0.193***	-0.068***
	(451.74)	(-220.96)
Constant	2.259***	2.499***
	(331.70)	(613.37)
Year FEs	Yes	Yes
County FEs	Yes	Yes
Six-digit NAICS code FEs	Yes	Yes
N	1,215,234	189,463
Adj. R^2	0.296	0.303

This table presents OLS estimates results. The sample contains SBA 7(a) data from 2004 to 2018, excluding firms in the Finance and Insurance (Two-digit NAICS=52). The dependent variables are the natural logarithm of time-to-maturity and the natural logarithm of interest rate. $Retail_j$ is a dummy variable, which equals one if the borrower of loan j is in the retail industry, and zero otherwise. Aft_t is a dummy variable, which equals one starting from 2010, and zero otherwise. Because loan interest rates are available starting from 2008, the sample period for Column 2 is limited to 2008 – 2012. Standard errors are clustered at the firm level, and all regressions include year, county, and NAICS code fixed effects. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4. 10 Trade credit around the CARD Act: retailer vs non-retailer

	Accounts payable$_{i,t}$/Total assets$_{i,t-1}$
Retail$_i$ × Aft$_t$	-0.022***
	(-2.64)
(Interest expense/Total liabilities)$_{i,t-1}$	-0.331***
	(-3.96)
(Sale/Total assets)$_{i,t-1}$	0.025***
	(3.92)
Size$_{i,t-1}$	-0.103***
	(-13.29)
(Cash/Total assets)$_{i,t-1}$	-0.022**
	(-2.53)
Leverage$_{i,t-1}$	0.193***
	(10.42)
ROA$_{i,t-1}$	-0.101***
	(-12.70)
(PPENT/Total assets)$_{i,t-1}$	-0.068*
	(-1.68)
Margin$_{i,t-1}$	-0.001
	(-1.07)
Age$_{i,t-1}$	0.037***
	(3.32)
Cashcycle$_{i,t-1}$	-0.000***
	(-3.44)
Constant	0.535***
	(11.16)
Firm FEs	Yes
Year FEs	Yes
N	57,137
Adj. R^2	0.759

This table presents OLS estimates of prepaid card balances regressions. The sample contains all firm-year observations from Compustat from 2004 to 2018, excluding firms in the Finance, Insurance and Real Estate (SIC 6000-6799). The dependent variable is (Accounts payable/Total assets)$_{i,t}$. Aft$_t$ is a dummy variable, which equals one starting from 2010, and zero otherwise. Retail$_i$ is a dummy variable, which equals one if firm i is in the retail industry, and zero otherwise. Other control variables are the same as in Table 4.5. Standard errors are clustered at the firm level, and all regressions include firm and year fixed effects. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4. 11 Prepaid card balance and debt covenant violations

	Unredeemed prepaid card balance$_{i,t}$/Total assets$_{i,t-1}$
Covenant violation$_{i,t+1}$	-0.016
	(-0.80)
Covenant violation$_{i,t}$	-0.004
	(-0.25)
Covenant violation$_{i,t-1}$	0.019**
	(2.33)
Covenant violation$_{i,t-2}$	0.005
	(0.81)
Covenant violation$_{i,t-3}$	0.017**
	(2.32)
Covenant violation$_{i,t-4}$	0.010**
	(2.21)
(Interest expense/Total liabilities)$_{i,t-1}$	0.188**
	(2.45)
Altman Z-score$_{i,t-1}$	-0.001**
	(-2.08)
(Sale/Total assets)$_{i,t-1}$	0.014***
	(4.05)
Size$_{i,t-1}$	-0.017***
	(-3.98)
(Cash/Total assets)$_{i,t-1}$	-0.021**
	(-2.55)
(Accounts payable/Total assets)$_{i,t-1}$	-0.103***
	(-4.08)
Leverage$_{i,t-1}$	-0.012
	(-1.29)
ROA$_{i,t-1}$	0.009
	(0.89)
(PPENT/Total assets)$_{i,t-1}$	-0.003
	(-0.19)
Age$_{i,t-1}$	0.017**
	(2.16)
Cashcycle$_{i,t-1}$	-0.000
	(-0.56)
Constant	0.095***

	(3.53)
Firm FEs	Yes
Year FEs	Yes
N	806
Adj. R^2	0.906

This table presents coefficient estimates from regressions of prepaid card balance to covenant violations. The covenant violation data from Roberts and Sufi (2009) is available in 2004 – 2012. The sample contains firm-year observations from 2004 to 2014. Covenant violation$_{i,t}$ equals one if firm i has a covenant violation during the year. Covenant violation$_{i,t-1}$ equals one if firm i has a covenant violation in the previous year. Covenant violation$_{i,t-2}$ equals one if firm i has a covenant violation two years ago. Covenant violation$_{i,t-3}$ equals one if firm i has a covenant violation three years ago. Covenant violation$_{i,t-4}$ equals one if firm i has a covenant violation four years ago. Other control variables are the same as in Table 4.5. Regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *, **, and *** significant at 10, 5, and 1%, respectively.

Table 4.12 Bankruptcy filing and prepaid card balance: penalized maximum likelihood estimation

	$Bankruptcy_{i,t}$
Unredeemed prepaid card $balance_{i,t-1}$/Total $assets_{i,t-1}$	16.429*
	(1.80)
Unredeemed prepaid card $balance_{i,t-2}$/Total $assets_{i,t-2}$	-35.341
	(-0.98)
Unredeemed prepaid card $balance_{i,t-3}$/Total $assets_{i,t-3}$	14.632
	(0.61)
$(\text{Sale/Total assets})_{i,t-1}$	0.948**
	(2.13)
$(\text{Cash/Total assets})_{i,t-1}$	-4.167
	(-1.38)
$Leverage_{i,t-1}$	3.624***
	(2.96)
$(\text{CF/Total assets})_{i,t-1}$	-8.225***
	(-4.10)
$(\text{Working capital/Total assets})_{i,t-1}$	0.985
	(0.65)
Constant	-6.177***
	(-3.35)
Year FE	Yes
N	988
Prob > chi2	0.030

The table tabulates coefficient estimates from Penalized Maximum Likelihood Estimation. $Bankruptcy_{i,t}$ equals one if year t is the last observation of firm i in Compustat and firm i files for bankruptcy within two years. $(\text{CF/Total assets})_{i,t-1}$ is the sum of income before extraordinary items and depreciation and amortization, divided by total assets. $(\text{Working capital/Total assets})_{i,t-1}$ is (Current assets-Current liabilities)/Total assets. I control for year fixed effects. *, **, and *** significant at 10, 5, and 1%, respectively.

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