Essays in Financial Fragility and Resolutions

Guangqian Pan

Submitted to the Research School of Finance, Actuarial Studies and Statistics,
College of Business and Economics
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy (Finance)
at the
AUSTRALIAN NATIONAL UNIVERSITY
July 2019
Student declaration

I declare that the PhD thesis reports finding from my own original research. Except where indicated otherwise, this thesis is my own work. It contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. © by Guangqian Pan 2019. The author grants to the Australian National University permission to reproduce and distribute copies of this thesis document in whole or in part.

Signature of Author: Guangqian Pan

Supervision Panel: Dr. Phong. T. H. Ngo, Chair
Professor Antje Berndt
Dr. Kentaro Asai
Acknowledgements

First and foremost, I would like to thank Phong Ngo, chair of my supervisory committee for his encouragement, guidance and wisdom over the duration of my doctoral studies. I would also thank my other supervisory committee members: Antje Berndt and Kentaro Asai for their comments on my work and general advice for the past five years. I am particularly grateful to my supervisory committee members for the “No”s that they have said to me. Those “No”s drive me to go beyond my comfort zones and to challenge myself. And those “No”s make the “Yes”s meaningful and joyful. For those many “No”s and a few “Yes”s, I am very extremely thankful for my supervisory committee members.

I also want to thank individuals who had direct influence on my research through their comments and criticisms in multiple occasions: Joshua Chan, Bruce Grundy, Iftekhar Hasan, Jean Helwege, Kun Li, Xin Liu, Robert Marquez, Shang-Jin Wei, Takeshi Yamada and Qiaoqiao Zhu.

I am also very grateful to the past and current members of ANU Economics Reading Group: Paul Amores, Minhee Chae, Tue Gorgens, Bob Gregory, Sanghyeok Lee, Anpeng Li, Ji Li, Joseph Marshan, Xin Meng, Kailing Shen, Peter Varela, Jilu Zhang and many casual participants in the past five years. I enjoyed and benefited significantly in many ways through numerous presentations and discussions with them.

Also, I would like to thank the Research School of Finance, Actuarial Studies and Statistics for giving me the opportunity to teach over the past five years. Thanks to the staff that I have had the pleasure to work with: Le Chang, Jo Drienko, Fei Huang, Raymond Liu and Abhinav Mehta. Thanks to those give me tremendous support, guidance and patience at the beginning of my teaching career: Jenni Bettman, Adam Butt, Tim Higgins, Michael Martin and Steve Sault.

Last but not least, my dearest thanks would go to my family, especially my parents. Without your supports, I could hardly imagine that I would achieve any of this.
Abstract

This thesis examines issues on financial fragility and possible resolutions. The key focus of three essays is to investigate how to implement both ex ante and ex post methods to avoid or mitigate the impact of financial fragility. The first essay explores the optimal reorganization bankruptcy choice for those firms experiencing financial difficulties. The second essay examines the role of creditor diversity on financial stability and its potential regulation implications. The third essay studies the role of information sharing on financial fragility induced by possible valuation runs.

The first essay finds pre-packaged reorganization (prepack) takes ex ante better firms through a shorter and less costly bankruptcy procedure compared to traditional Chapter 11 but leads to more refiling. To explain this phenomenon, I propose an information acquisition model where creditors trade higher bankruptcy costs under traditional reorganization with higher accuracy in filtering inefficient from efficient firms. The prepack decision is governed by the value of the signal that a firm can acquire under traditional Chapter 11. Empirically, firms with better information and higher downside risks choose traditional reorganization. These firms subsequently have a lower rate of emergence but a higher survival rate.

The second essay examines the effectiveness of bank regulation in the light of creditor diversity. We focus on a bank’s value generation through the interaction of its issuance of securities with different risk levels, matching between securities and creditors, and capital buffer. Our calibration and evidence suggest even a well-capitalized bank cannot eliminate financial fragility in the absence of creditor diversity. We find capital regulation is only effective when a bank can save financing costs by matching the riskiness of securities and the risk tolerance of diverse creditors. If financial fragility is persistent, we suggest liquidity regulation can mitigate excessive risk-taking.
In the presence of multiple equilibria, financial market may experience valuation shock which shifts the market from high credit supply equilibrium to low credit supply equilibrium, causing sharp declines in financing and welfare. The third essay studies the impact of information sharing to this financial fragility. I find information sharing can mitigate the magnitude of the credit supply reduction; meanwhile increases market’s fragility, i.e. the likelihood of such reduction. Since information sharing encourages valuation and discourages unsophisticated investments, sophisticated investors would strictly prefer information sharing, which could lead to a suboptimal social outcome. From a social planner’s perspective, optimal choice of information sharing should be countercyclical.
CONTENTS

1. Chapter 1: Patience is a virtue: Evidence from insolvency .......................................................... 10
   1.1 Introduction ............................................................................................................................... 12
   1.2 Background .............................................................................................................................. 17
      1.2.1 Introduction to Prepack .................................................................................................. 17
      1.2.2 Literature and Contribution ......................................................................................... 21
      1.2.3 Prepack Refiling Puzzle ............................................................................................... 23
   1.3 Model ...................................................................................................................................... 26
      1.3.1 Assumptions .................................................................................................................... 26
      1.3.2 Baseline Model ............................................................................................................... 27
      1.3.3 Bargaining Power and Conflicts .................................................................................. 33
      1.3.4 Debt-Equity Conflicts ................................................................................................... 35
   1.4 Data ........................................................................................................................................ 37
   1.5 Empirical Test .......................................................................................................................... 39
      1.5.1 Refiling ............................................................................................................................ 41
      1.5.2 Emergence ....................................................................................................................... 47
      1.5.3 Role of Information ......................................................................................................... 48
   1.6 Robustness Checks .................................................................................................................. 51
      1.6.1 Managerial Controls, Costs and Investment ................................................................. 51
      1.6.2 Fixed Effects and Judicial Controls............................................................................... 54
   1.7 Conclusion ............................................................................................................................... 55
   1.8 References ................................................................................................................................ 57
   1.9 Appendix ................................................................................................................................ 60
      1.9.1 Appendix 1 ....................................................................................................................... 60
      1.9.2 Appendix 2 ....................................................................................................................... 63
   1.10 Tables and Figures .................................................................................................................. 66
      Figure 1: Rise of Pre-packaged Chapter 11 ............................................................................ 66
      Figure 2 ..................................................................................................................................... 67
      Figure 3 ..................................................................................................................................... 68
      Table 1 ....................................................................................................................................... 69
      Figure 4 ..................................................................................................................................... 71
      Figure 5 ..................................................................................................................................... 72
      Figure 6 ..................................................................................................................................... 73
2. Chapter 2: Risk Sharing, Creditor Diversity, and Bank Regulation ............................................ 97
   2.1 Introduction ................................................................................................................................. 99
   2.1.1 Institutional detail ...................................................................................................................... 104
   2.2 Relation to the literature ............................................................................................................ 106
   2.3 Model ......................................................................................................................................... 109
      2.3.1 Overview .................................................................................................................................. 109
      2.3.2 Timing ...................................................................................................................................... 111
      2.3.3 Key frictions .............................................................................................................................. 112
      2.3.4 The bank’s risk choice .............................................................................................................. 114
      2.3.5 The depositors’ investment choice and the bank’s pricing strategy ......................................... 115
      2.3.6 The bank’s issuance of demand deposits ................................................................................. 118
      2.3.7 Equilibrium .............................................................................................................................. 119
      2.3.8 Key channel for achieving financial stability ........................................................................... 121
      2.3.9 Efficiency ................................................................................................................................. 124
   2.4 Numerical examples .................................................................................................................... 126
      2.4.1 Parameters used for the benchmark case ............................................................................... 126
      2.4.2 Financial regulations ............................................................................................................... 126
      2.4.3 Results ..................................................................................................................................... 127
   2.5 Empirical evidence ..................................................................................................................... 132
      2.5.1 Data ......................................................................................................................................... 132
      2.5.2 Empirical analysis .................................................................................................................... 137
   2.6 Discussion .................................................................................................................................... 139
   2.7 References .................................................................................................................................... 141
   2.8 Appendix ...................................................................................................................................... 144
      2.8.1 A.1 Proofs ................................................................................................................................. 144
      2.8.2 A.2 Continuous distribution of relative risk aversion .............................................................. 147
      2.8.3 A.3 Robustness ......................................................................................................................... 150
3. Chapter 3: Information Sharing and Financial Fragility

3.1 Introduction .......................................................................................... 170
3.2 Model setting ...................................................................................... 174
3.3 Exogenous information sharing level ..................................................... 177
  3.3.1 Information sharing ........................................................................ 178
  3.3.2 Equilibrium .................................................................................... 179
  3.3.3 Welfare analysis ............................................................................ 180
  3.3.4 Impacts of valuation shocks .......................................................... 185
  3.3.5 Optimal information sharing level .................................................. 189
3.4 Information sharing as a choice ............................................................ 191
3.5 Discussions ........................................................................................... 193
  3.5.1 Noisy valuation ............................................................................ 193
  3.5.2 Costly dilution .............................................................................. 194
  3.5.3 Start-up financing .......................................................................... 195
3.6 Conclusion ............................................................................................ 195
3.7 Reference ............................................................................................... 197
3.8 Appendix ............................................................................................... 199
  3.8.1 Appendix A .................................................................................. 199
  3.8.2 Appendix B .................................................................................. 203
3.8.3 Appendix C: Noisy valuation ................................................................. 204

3.9 Tables and Figures .................................................................................. 213

Table 1: Features of four equilibria .............................................................. 213
Table 2: Cost constraints and market quality constraints of four equilibriums .................................................................................. 214
Figure 1: Equilibria regions in quality-cost ($\lambda, c$) plane ......................... 215
Figure 2: Welfare changes comparing a partial information sharing regime and a complete information sharing regime .......................................................... 216
Figure 3: Valuation, sophisticated investors' profits and social welfare in pure valuation/pooling region ................................................................. 217
Figure 4: Increasing information sharing in pure valuation/pooling region ...... 218
Figure 5: Valuation, sophisticated investors' profits and social welfare in mixed/pooling region ................................................................. 219
Figure 6: Increasing information sharing in mixed/pooling region .................. 220
Figure 7: Changes in minimum shock required and social welfare drop with regard to information sharing level ................................................................. 221
Figure 8: Expected drop in welfare with regard to information sharing in different business cycles .................................................................................. 222
Figure A1: Noisy valuation ................................................................. 223
1. Chapter 1: Patience is a virtue: Evidence from insolvency
Patience is a virtue: Evidence from insolvency

Guangqian Pan*  

Abstract

Pre-packaged reorganization (prepack) takes ex ante better firms through a shorter and less costly bankruptcy procedure compared to traditional Chapter 11 but leads to more refiling. To explain this phenomenon, we propose an information acquisition model where creditors trade higher bankruptcy costs under traditional reorganization with higher accuracy in filtering inefficient from efficient firms. The prepack decision is governed by the value of the signal that a firm can acquire under traditional Chapter 11. Empirically, firms with better information and higher downside risks choose traditional reorganization. These firms subsequently have a lower rate of emergence but a higher survival rate.

Keywords: Chapter 11; Information acquisition; Bankruptcy efficiency; Prepacks; Post-bankruptcy performance.

JEL classification: D83 G33 G3

* Guangqian Pan: College of Business and Economics, Australian Nation University, 26C Kingsley Street, Acton ACT 2601, Australia (e-mail: guangqian.pan@anu.edu.au). This paper is based on a chapter of my PhD dissertation at Australian National University, College of Business and Economics. For helpful comments, I am particularly grateful to my supervisors, Phong Ngo (Chair), Kentaro Asai and Antje Berndt, and I thank Mardi Dungey, Espen Eckbo, Ron Giammarino, Bruce Grundy, Iftekhar Hasan, Jean Helwege, Chang Mo Kang, Wei Wang, Shang-Jin Wei, and Tak-Yuen Wong, in addition to the participants in seminars and conferences at the FMA Annual Meeting 2017, AsianFA 2018, 8th FIRN Annual Conference, Australasian Finance and Banking Conference PhD Forum 2018, New Zealand Finance Meeting 2018, the Australian National University, University of Melbourne, University of Queensland, University of Sydney, University of Tasmania, and University of Technology Sydney. All views and remaining errors are my own.
1.1 Introduction

In 1986, Crystal Oil Company filed the first known pre-packaged bankruptcy (prepack), and it took only three months for the court to confirm its plan of reorganization. Since then, prepack has become popular as a bankruptcy procedure. Figure 1 shows that since the early 1990s, prepack has become an important part of the bankruptcy landscape. Specially, since 2009, prepack has comprised half of large Chapter 11 cases. Moreover, the most recent U.S. energy sector bankruptcy wave demonstrates that prepack has become a major tool to reach debt-restructuring deals\(^1\). Regulators\(^2\), academics\(^3\) and practitioners\(^4\) share a positive view about prepack, praising its shorter procedure and lower costs than traditional Chapter 11 bankruptcy. Nevertheless, in recent years, some firms going through prepack experienced substantial asset losses afterwards. For instance, Dex Media, Inc.’s asset value declined almost 90% after completing five prepack deals within seven years. Despite these contrasting facts, other characteristics of these two different reorganization processes are largely unexplored. What types of firms choose prepack? How does this choice impact firms’ outcomes during and after bankruptcy? The answers to these economically important questions remain at best inconclusive, and this paper endeavors to offer some insights.

This paper documents an important downside of prepack. Figure 2.2 shows that the industry-adjusted average refiling rate within 5 years for firms that previously filed via prepack is 8% greater than the rate for firms that previously filed via traditional Chapter 11. Previous theories fail to explain why this seemingly beneficial bankruptcy process would lead to a higher refiling


\(^2\) The U.S. Securities and Exchange Commission’s (SEC) investor publications suggest that prepack “shortens and simplifies the process, saving the company money”. See: https://www.sec.gov/investor/pubs/bankrupt.htm

\(^3\) There is a consensus in the bankruptcy literature that the prepack has a shorter duration and lower direct costs than traditional Chapter 11 (Betker, 1995; Ivashina, Iverson, & Smith, 2016; Tashjian, Lease, & McConnell, 1996).

\(^4\) A recent article in a practitioner’s journal, the American Bankruptcy Institution Journal, also claims that pre-packaged Chapter 11 “can provide a favorable structure to minimize a debtor's time in Chapter 11, reduce costs and operational disruptions, preserve estate value, and still secure the benefits of a Chapter 11 plan.”
rate for firms. For example, one conventional view holds that the choice between prepack and traditional Chapter 11 bankruptcy is based on the complexity of the case. Firms with dispersed claimholders find it more difficult to achieve consent on their reorganization plan, and they therefore have to go through traditional Chapter 11 despite its higher cost (McConnell & Servaes, 1991). However, recent bankruptcy cases show a clear trend that large and structurally sophisticated firms (e.g., General Motors 2009; CIT Group Inc. 2009; Halcón Resources Corp 2016) are adopting prepack as a reorganization mechanism. Moreover, the mechanism seems fail to explain why firms with simpler structures tend to fail more post-bankruptcy. Accordingly, an examination of the determinants of the choice between pre-packaged Chapter 11 and traditional Chapter 11 seems necessary.

[Insert Figure 1]

[Insert Figure 2]

The major contribution of this paper is to study the decision-making mechanisms of choosing between traditional Chapter 11 and prepack based on an information acquisition setup. We challenge the idea that pre-packaged Chapter 11 bankruptcy is always superior to traditional Chapter 11 bankruptcy by proposing an information and cost trade-off model for the Chapter 11 bankruptcy procedure. In the baseline model, traditional Chapter 11 bankruptcy is associated with higher costs to gather a signal about firms’ future performance during their bankruptcy procedure. Under traditional Chapter 11, continuation decisions are made in two consecutive periods. Creditors observe the firm’s liquidity condition in the first period and a noisy signal in the second period. A firm only continues if there is a good liquidity condition in the first period and if there is a good signal about firm’s solvency state in the second period. In prepack, a firm continues if there is a good liquidity condition in the first period without

---

5 Such a trade-off mechanism is commonly assumed to individuals in the market efficiency literature, e.g., (Verrecchia, 1982).
investigating its long-run efficiency. Therefore, traditional Chapter 11 bankruptcy is better able to filter inefficient from efficient firms, whereas prepack skips the signaling period during bankruptcy and reduces cost. During bankruptcy, a wide range of time-varying information about the bankrupt firm is acquired to ensure that the firm is using the appropriate resolution. For this reason, this paper emphasizes that information is the key difference in the comparison between traditional Chapter 11 and prepack. Consequently, the trade-off mechanism between the higher cost and the value of the signal dominates the decision of whether to choose prepack or traditional Chapter 11.

Second, the model sheds lights on two key determinants governing the choice whether to prepack. In the baseline model, the value of a signal is associated with its noisiness and the future downside risk of the bankrupted firms. If firms receive noisier signals, the likelihood of errors in creditors’ continuation decision is increased. Both the chance of liquidating efficient firms and the chance of letting inefficient firms emerge from bankruptcy increase, and the expected value of the signal decreases. Thus, these firms would prefer prepack because of its cost savings. The firm’s future downside risks would also explain the choice of prepack. A firm that is less likely to be insolvent benefits less from the signal because there is little need for creditors to filter. Therefore, these firms would prefer prepack.

When we extend the model to multiple parties, conflicts may arise. However, these conflicts can be eliminated by wealth transfer mechanisms and ultimately have no impact on the choice of bankruptcy procedures if all claimholders hold the same beliefs⁶. In this case, social welfare remains unchanged, although a violation of the Absolute Priority Rule (APR) arises because of the wealth transfer. Such a violation is ex-post efficient for social welfare. In the case that one party (e.g., the equity holder) dominates the decision-making, the bankruptcy choice

---

⁶ Under heterogeneous beliefs, wealth transfer can be welfare destroying.
depends on the focus of court supervision. The result suggests a court focusing on the right bankruptcy procedure can always achieve a socially optimal bankruptcy choice while it is not always true for a court focusing on deviation from APR.

Third, the model predicts a range of different bankruptcy outcomes through prepack and traditional Chapter 11. Regarding the emergence rate, only illiquid firms fail to emerge from prepack. In the contrast, traditional Chapter 11 liquidates not only illiquid firms but also firms receiving a bad signal. Thus, we expect prepack to have a higher emergence rate. Nevertheless, traditional Chapter 11 partially filters out inefficient firms through a noisy signal. Therefore, firms that emerge from traditional Chapter 11 have a higher survival rate and lower ex-post downside risk.

Finally, this paper empirically tests the predictions of the model and finds supporting evidence. Our model predicts firms with high noisiness and low future downside risk would prefer prepack. Empirically, we find that firms with higher intangible assets and higher Altman’s Z-scores tend to choose pre-packaged Chapter 11 bankruptcy, which supports our prediction. Intangible assets are difficult to value (Edmans, 2011; Kumar, 2009; Lev, 2004). Thus, intangible assets increase the noisiness of the signal and make traditional Chapter 11 bankruptcy less favorable. Regarding firms’ risk features, Figure 2.1 shows that the industry-adjusted average Z-score index of firms filing under prepack is 1.9 higher than that of traditional Chapter 11 firms. A higher Z-score suggests that prepack firms are ex ante higher-quality firms with less insolvency concerns. Therefore, obtaining additional information through a costly traditional Chapter 11 bankruptcy is less attractive to those firms.

Our model also predicts firms under traditional Chapter 11 bankruptcy are less likely to emerge during bankruptcy and have a better survival rate post-bankruptcy. Empirically, a lower emergence rate can mean fewer good firms emerge, fewer bad firms emerge or both. A direct test of whether traditional Chapter 11 preserves more good firms is empirically impossible,
because once firms are liquidated, their true solvency states are unobservable. Instead, this paper adopts an indirect method by establishing the facts that traditional Chapter 11 firms have worse pre-bankruptcy characteristics but better post-bankruptcy characteristics. The results are robust to the inclusion of various bankruptcy predictors in the existing literature. This result indirectly implies that traditional Chapter 11 preserves a higher proportion of good firms than prepack does through a more robust filtering scheme. This is consistent with our model predictions about bankruptcy outcomes.

Overall, we show that prepack decisions are governed by the costs of information acquisition during the traditional Chapter 11 process: higher costs imply prepack is more likely to be used. Our model is able to rationalize the previously ignored fact that while prepack is associated with a shorter duration and lower costs, firms choosing this process are also more likely to refile for bankruptcy in the future. Our model also predicts that firms choosing prepack are more likely to emerge from bankruptcy. Finally, firms with high noisiness and low future downside risk would prefer prepack. We find empirical support for these predictions. Firms with higher intangible assets and higher Altman’s Z-scores tend to choose prepack, which supports high noisiness and low future downside risk as the determinants of prepack. The higher emerging rate and higher refining rate in prepack are also consistent with our prediction.

The key contribution of this paper is to highlight the role of costly information acquisition during traditional Chapter 11, and this information can indeed improve the accuracy of the bankruptcy process in filtering the good firms from the bad. John, Mateti, and Vasudevan (2013) model reorganization decisions coping with a range of features, including prepack. However, unlike our model, their model provides little implications about post-bankruptcy outcomes.

The rest part of this paper is structured as follows. Section I introduces the institutional details of prepack and the related literature. Section II discusses the model. Section III explains the
data and Section IV demonstrates the empirical tests. Section V covers the robustness tests. Section VI concludes.

1.2 Background

1.2.1 Introduction to Prepack

U.S. Bankruptcy Code Chapter 11 is widely believed to be an important part of the economy, as it aims to allow good firms to survive through financial distress. Criticisms of Chapter 11 suggest that the process is inefficient in achieving that goal since it allows more economically nonviable firms to survive under court protection. These concerns highlight the importance of the efficiency of Chapter 11.

Meanwhile, the landscape of bankruptcy has changed dramatically with related legislation changes and innovations, one important feature of which is the rise of prepack. Unlike traditional Chapter 11, under which claimholders must form plans and seek agreement after filing bankruptcy, prepack allows firms to obtain consent before bankruptcy filing and significantly shortens the process.

More specifically, under U.S. Bankruptcy Code Chapter 11, firms enter the Chapter 11 bankruptcy process when the debtor (voluntary bankruptcy) or creditors (involuntary bankruptcy) file a bankruptcy petition for court protection. After the filing, the firm enters a state of automatic stay that temporarily ceases creditors’ debt collection actions until the case can be resolved. The length of the automatic stay can vary from 120 days up to 18 months, given the court’s permission for extension. Meanwhile, debtors or creditors can file a disclosure statement and a plan of reorganization. The plan of reorganization outlines the proposed recoveries for different classes of claimholders and the blueprint for how they can recover through the reorganization process. A disclosure statement is required to disclose adequate information about the firm such that all relevant parties can make their decision about the plan
of reorganization. After the court approves the disclosure statement, all classes of claimholders can vote to accept or reject the plan. The centerpiece of the reorganization process is the establishment of a plan of reorganization agreed upon by the majority of the parties. The bankruptcy court oversees confirming such a plan by assessing the plan votes. The basic guideline for the confirmation of a successful plan requires that at least one class of non-insiders who hold impaired claims (i.e., claims that are not fully recovered or whose contractual details are modified) accept the plan. 11 U.S.C. § 1129(a) (10). An entire class of claims is deemed to accept a plan if the plan is accepted by creditors that hold at least two-thirds of the amount and more than one-half the number of the allowed claims in the class. 11 U.S.C. § 1126(c). Once a plan is confirmed, the court will further oversee its implementation until the firm emerges from bankruptcy and the case is closed. Figure 3 outlines the process of a traditional Chapter 11 procedure.

[Insert Figure 3]

Prepack differs from traditional Chapter 11 because the firm’s consent to the plan occurs before the filing of bankruptcy. This facilitates the bankruptcy procedure for two reasons. First, by law, the acceptance or rejection of the prepack plan no longer needs to wait until the court approves the written disclosure statement. Rather, it skips the filing to the plan submission period, which Bris, Welch, and Zhu (2006) report takes 207 days on average. Second, prepack is pre-voted or has pre-agreed votes. Therefore, it is easier for the votes to pass the court’s confirmation. Consequently, this process shortens the days from plan submission to confirmation, which takes an average of 225 days (Bris et al., 2006). Figure 1 shows that prepack has become popular in recent years, especially after 2009. In a bankruptcy survey conducted among restructuring professionals in 2010, 97% of respondents suggest that prepack
should be a long-term component in the Chapter 11 framework. Regulators such as the SEC suggest that prepack “shortens and simplifies the process, saving the company money”. Globally, there is a quickly growing trend of adopting pre-packaged reorganization as an alternative bankruptcy method to enable economically efficient firms to continue as going concerns.

Despite its popularity, there is a relatively small body of literature about prepack. A well-documented fact is that compared to traditional Chapter 11, prepack has a significantly shorter duration in the bankruptcy process (Betker, 1995; Ivashina et al., 2016; Tashjian et al., 1996), and the majority of the literature emphasizes that this shorter duration tends to lead to relatively lower costs (both direct costs and indirect costs) (Thorburn, 2000). In contrast, the determinants of prepack and the characteristics of prepack firms remain unclear in the current literature (Chatterjee, Dhillon, & Ramirez, 1996; John et al., 2013; McConnell, Lease, & Tashjian, 1996; McConnell & Servaes, 1991; Tashjian et al., 1996).

Whereas these studies try to explore some features of prepack, none of them provide a framework for analyzing a firm’s prepack choice or provide tractable predictions. This paper fills in this gap and introduces information acquisition into the decision mechanism. Given the lack of understanding of prepack and its frequent appearance, studies in the bankruptcy literature treat prepack cases very differently. These different empirical treatments create an additional motivation to conduct a comprehensive study on prepack and understand its fundamental differences from traditional Chapter 11.

---


8 Countries such as Italy, France, Poland, Czech Republic and Estonia have introduced different forms of pre-arranged reorganization through bankruptcy reforms (Cirmizi, Klapper, & Uttamchandani, 2011).

9 Some studies choose to exclude prepacks because of their distinct nature in duration (Bris et al., 2006; Dahiya, John, Puri, & Ramirez, 2003). Some include them because they are under court supervision, as in traditional Chapter 11, and use prepack as a dummy in the analysis to separate the effects (Adler, Capkun, & Weiss, 2013; Jiang, Li, & Wang, 2012; Kalay, Singhal, & Tashjian, 2007). Others (e.g., Ivashina et al. (2016)) use pre-packaged Chapter 11 as a positive indicator for bankruptcy efficiency when they study debt ownership concentration.
Information is a key difference that is often overlooked in the comparison between traditional Chapter 11 and prepack. Our main contribution thus is to highlight the important role of information acquisition during the bankruptcy process and show that it has a significant bearing not only on the choice of procedure type but also on ex-post outcomes. A wide range of information about the bankrupt firm is acquired during bankruptcy to ensure that the appropriate resolution is being employed. Particularly, from the legal perspective, lawmakers emphasize the importance of information acquisition for the welfare of all relevant parties. For example, the U.S. Bankruptcy code section 1125 requires the firm to provide “adequate information” in a disclosure statement to all claimholders before they vote for the plan. This requirement demonstrates the importance of information acquisition in the reorganization procedure\textsuperscript{10}.

Moreover, most of the information is time varying. Investors will receive the latest bankruptcy news during bankruptcy cases. U.S. bankruptcy law and regulations require firms to submit monthly operating reports, which provide time-varying information during the bankruptcy process. 11 U.S.C. §§ 1106, 1107; Fed. R. Bankr. P. 2015(a). Moreover, disclosure statements always involve a valuation of the firm, which depends on the information available at the time. Unofficially, firms strategically wait to reveal more information before their bankruptcy decisions. For example, in retail bankruptcy cases, the retailer usually makes the bankruptcy decision after holiday sales\textsuperscript{11}. These facts suggest that information acquisition is

\textsuperscript{10} With respect to prepack, Federal Rules of Bankruptcy Procedure 3018 (b) requires the decision time of the prepack vote to not be “unreasonably short.” The U.S. Bankruptcy Court for the Southern District of New York further clarifies that being not “unreasonably short” is “21 days for the majority of claims and 14 days for unlisted securities”. Indiana has adopted a similar guideline (Zide, O’Neill, & Blank, 2015).

\textsuperscript{11} For instance, Circuit City was once the second-largest consumer electronics retailer in the U.S. It filed for Chapter 11 on November 10, 2008, with $3.4 billion in assets. After an unsuccessful holiday sale season, it failed to find appropriate buyers and converted from Chapter 11 to Chapter 7 on January 16, 2009. Similarly, Dick Smith was the second-largest consumer electronics retailer in Australia. On January 4, 2016, Dick Smith’s chairman announced “Sales and cash generation in December were below management expectations, continuing a trend experienced during 2015,” and soon afterwards, its creditors put it into receivership on January 5, 2016.
important during the bankruptcy procedure, and the length of bankruptcy can directly impact
the information acquired.

1.2.2 Literature and Contribution

This paper is part of a large body of literature that discusses the efficiency of Chapter 11. Ideally, we want economically viable firms to restructure through Chapter 11 and inefficient firms to not emerge from bankruptcy. However, both theoretical and empirical studies provide sparse results on the efficiency of Chapter 11.

Theoretically, we compare the efficiency of the filtering mechanism between two Chapter 11 procedures that both involve court supervision, which mitigates the creditor holdout problems that usually occur in private workout. While one can argue the same information acquisition trade-off can exist for the choice between private workout and court restructuring, focusing on two forms of court supervised bankruptcy procedures allows us to examine the mechanism without creditor holdout concerns. Empirically, despite the ongoing debate regarding the costs and benefits of Chapter 11 (Eberhart, Altman, & Aggarwal, 1999; Gertner & Scharfstein, 1991; Hotchkiss, 1995; Kalay et al., 2007; Rodano, Serrano-Velarde, & Tarantino, 2016), an unexplored issue is how creditors can acquire information about whether the firm is financially distressed or economically efficient during bankruptcy. Discussion of this issue is essential to understand the efficiency and externality of bankruptcy costs related to Chapter 11. This paper both theoretically and empirically examines this issue and explains the information acquisition within two reorganization mechanisms.

Our model neglects the role of managers in the model, which departs from a large body of literature that emphasizes the importance of managerial roles in bankruptcy decisions (Adler et al., 2013; Hotchkiss, 1995; White, 1994). There are a few reasons for this assumption. Generally, studies include the role of managers based on two key aspects, i.e., information
asymmetry and divergent interests among managers, shareholders and creditors, which lead to value destruction activities for firms.

Regarding the first point, fundamentally, such studies assume that managers fully understand the economic viability of the firm, whereas creditors do not obtain such information. However, firms’ economic outcomes could be difficult for anyone to predict, even for managers. For instance, the onset of the great recession was unexpected for most (if not all) managers, and the number of bankruptcy cases surged significantly after the Global Financial Crisis (GFC). This fact establishes that there is a sizable level of uncertainty for all parties who have interests in the firms and challenges the foundation of the information asymmetry story.

Regarding incentives, recent studies provide evidence that creditors have been gaining bargaining power over managers since the 1990s (Adler et al., 2013; Hackbarth, Haselmann, & Schoenherr, 2015). In bankruptcy law, “cram down” limits the equity holder’s ability to bargain with creditors. Finally, for insolvent firms, creditors generally become new equity holders and have controlling rights regarding manager turnover both during and after bankruptcy. Thus, the interests of managers and creditors are more allied. Therefore, for the most part of our paper, we assume that both managers and creditors coordinate to acquire information in the absence of conflicts of interest. Nevertheless, an extension about debt-equity conflicts is also examined in Section II.

The most relevant article to this paper is that of Eckbo and Thorburn (2008) regarding the Swedish auction system. They find that post-bankruptcy operating performance for firms using prepack auctions is not significantly different from that of non-prepack firms; however, the refiling rate is significantly higher. They interpret the results as an outcome of risky liquidation preemption. Creditors rush into prepack to avoid fire-sale loss in liquidation, and the motivation is higher for firms that have higher liquidation risks and they tend to fail more post-bankruptcy. Although the refiling results from empirical tests may appear similar, this paper is different
from their findings due to the legal environment and sample characteristics\textsuperscript{12}. Whereas the liquidation preemption argument could explain prepack auctions in Sweden, information acquisition theory provides a more general argument for prepack reorganization. Nevertheless, our empirical analysis in Section IV also examines the liquidation preemption hypothesis in our dataset.

1.2.3 Prepack Refiling Puzzle

Table 1 illustrates firms’ different features and bankruptcy outcomes through the two bankruptcy procedures. Consistent with previous studies, we find that prepack has a significantly shorter duration and lower direct costs than traditional bankruptcy. On average, firms that follow traditional Chapter 11 spend 678 days in bankruptcy (from the bankruptcy filing date to the confirmation date), while prepack only takes 184 days. Further, the direct costs consist of 3.51\% of assets at filing for traditional Chapter 11 and only 2.04\% of assets at filing for prepack. The result also suggests that prepack firms are generally better firms. Panel

\textsuperscript{12} First, the prepack bankruptcy concepts are fundamentally different. The prepack auction in the Swedish system is a cash auction process overseen by a trustee appointed to take control of the firm (Thorburn, 2000). The filing is subject to the approval of secured creditors. Therefore, Eckbo and Thorburn (2008) argue prepack auction is similar to private workouts. Every firm went through that prepack auction was sold as going concerns. In contrast, prepack reorganization in the U.S. system is a court supervised restructuring process. Management can continue to control the firm’s operations, and the ownership of the firm does not necessarily change. Some firms fail to emerge from the prepack procedure. Second, the outside options for two prepacks are different. For a prepack going-concern auction, the more likely alternative is a piece-meal sale, which is close to liquidation and subject to buyers’ demand. For prepack Chapter 11, the more likely alternative is traditional Chapter 11 or a private workout, which is a decision subject to agreement by the majority of creditors. Third, the judicial system is very different with respect to the bankruptcy acts. For example, insolvency is required under Swedish bankruptcy but not U.S. bankruptcy. After the 1978 Bankruptcy Reform Act, insolvency is no longer needed for U.S. firms to claim bankruptcy, which raises concerns of both illiquidity and insolvency issues in Chapter 11 bankruptcy (Hackbarth et al., 2015). Finally, our sample characteristics are different from those of the Eckbo and Thorburn (2008) sample, as the sample firms in their paper are all private firms with an average pre-filing sale value of $8 million (in 2007 dollars), and the auction is constrained to cash only (Thorburn, 2000). This cash settlement restriction may endogenously restrict its application to large deals. The data in this paper relate to public firms with at least $100 million (in 1980 dollar) in assets, and all-cash settlements are rare. Firm size could matter, as Morrison (2007) finds that continuation bias disappeared in small business Chapter 11 cases. In a separate study also analyzing the Swedish bankruptcy system, Thorburn (2000) finds that the system may be efficient for small firms. The private or public nature of a firm may affect the results, as private firms are more likely to suffer fire-sale losses than public firms because of the lack of information available to the public.
B of Table 1 indicates that prepack firms have higher employee efficiency\textsuperscript{13}, lower asset volatility\textsuperscript{14}, a higher Altman’s Z-score\textsuperscript{15} and higher profitability at filing. Hence, firms choosing prepack are in relatively better financial positions and use labor more efficiently.

\textbf{[Insert Table 1]}

The more interesting findings lie in the post-bankruptcy outcomes. The mean values indicate that prepack dramatically increases the likelihood of refiling within 5 years after the firms emerge. The refiling rate within 5 years post-bankruptcy for firms emerging from prepack is 9 percentage points higher than that for firms emerging from traditional Chapter 11. This creates a “prepack refiling puzzle”. If the bankruptcy procedure is merely a redistribution or value-destroying process, based on previous findings, better firms going through a faster and less costly reorganization process (i.e., prepack) should perform better post-bankruptcy. The significantly higher refiling rate for prepack suggests that despite its lower costs and shorter duration, it misses some value-enhancing functions involved in traditional Chapter 11.

Figure 4 shows the refiling pattern within 5 years after emergence for traditional vs prepack. We can observe two noticeable facts. First, compared to traditional Chapter 11, prepack tends to have a higher refiling rate, especially during the third and fourth years after firms emerge. Specifically, the bankruptcy rate for prepack in the third year is three times greater than that for traditional Chapter 11 and two times greater in the fourth year. That is, prepack firms suffer much more severe solvency problems than traditional bankruptcy post-bankruptcy. However, in contrast to Eckbo and Thorburn (2008) finding in the Swedish auction system, the refiling

\textsuperscript{13} Employee efficiency measures how much each employee in the firm can contribute to sales as a proxy for labour efficiency. After we adjust for industry, on average, employees in firms that choose prepack create $0.4 million more per person than employees in firms that choose traditional Chapter 11.

\textsuperscript{14} I use the Merton (1974) model to calculate the asset volatility of the firms one year before bankruptcy. I find that firms using prepack are less volatile than those filing under traditional Chapter 11.

\textsuperscript{15} Furthermore, I calculate Altman’s Z-scores, which are an indicator of a firm’s financial position, and I find a significant difference between firms choosing prepack and firms choosing traditional Chapter 11. Specifically, firms that choose prepack have an industry-adjusted average Z-score of 0.85, compared to -1.04 for those filing under traditional Chapter 11.
rate within the first two years is actually lower for prepack than for traditional Chapter 11. Second, the timing of refiling is an equally interesting result. Approximately 11% of the firms emerging from prepack refiled during year 3, another 6% in year 4 and fewer still in year 5. However, we observe that the refiling rate for firms through traditional Chapter 11 peaks in year 2 and gently decreases in later years. The time gap between the two refiling peaks for the two Chapter 11 processes closely matches their difference in days spent in bankruptcy. We suspect that this difference is not a coincidence; rather, it reflects that the timing for the long-term value (i.e., solvency) realization may take 4–5 years. In the case of traditional Chapter 11, firms spend 2 years in bankruptcy and another 2 years after they emerge before realizing their solvency. In prepack, firms take less than one year to process the bankruptcy and three to four years to realize their solvency. This result is consistent with the information acquisition model that we propose later, and to the best of our knowledge, no existing theories can explain it.

[Insert Figure 4]

Figure 5 presents the post-bankruptcy EBIT margin for both traditional Chapter 11 and prepack. On average, firms in every percentile under both Chapter 11 processes experience a decline in their margins in about year 3 and recover in later years. The timing of this decline is consistent with the findings of (Hotchkiss, 1995) study on the post-bankruptcy performance of firms emerging from Chapter 11. Interestingly, the dispersion of the margins also increases with the margins’ decline and decreases after they recover. Notably, the profitability percentiles are more dispersed for prepack, thus indicating that the dispersion in firms’ qualities is higher than that under traditional Chapter 11. In addition, such difference in dispersion is greatest in the lower percentiles. This result suggests that for those firms following prepack, the post-bankruptcy downside risks are much higher, which is consistent with Eckbo and Thorburn (2008) finding and supports our hypothesis about firms’ long-term value realization post-bankruptcy. Much fewer traditional Chapter 11 firms struggle in terms of performance, with
shorter periods of underperformance and faster recovery. This result indicates that the aggregate qualities for firms emerging from traditional Chapter 11 are higher.

1.3 Model

In this section, we introduce the information acquisition model for the two Chapter 11 bankruptcy procedures. It starts with a simple discrete time, single-decision-maker model. The key findings are that traditional Chapter 11 bankruptcy is associated with higher costs to gather a signal about firms’ future performance during their bankruptcy procedure. The value of the signal is associated with its noisiness and the future downside risk of the bankrupted firms. Firms that emerge from traditional Chapter 11 would have a higher survival rate and lower ex-post downside risk compared to prepack. Later, multiple decision makers are introduced, and the aforementioned results still hold16.

1.3.1 Assumptions

One important issue that we want to clarify is the difference between insolvency and illiquidity. In the U.S., when a distressed firm enters a bankruptcy process under Chapter 11, it may either face liquidity or solvency issues17. Insolvency represents long term incapacity to meet debts18. In contrast, illiquidity represents a temporary incapacity to meet debts. Other alternative names for insolvent and solvent firms could be economically inefficient or non-

---

16 We also provide a continuous model in the Online Appendix, and the results still hold.
17 Insolvency law varies across countries and across time. In Sweden, bankruptcy law requires creditors to prove a firm’s insolvency if the filing is creditor initiated (Eckbo & Thorburn, 2008). In the U.S., before the bankruptcy reform of 1978, insolvency was required for firms. After the reform, Bradley and Rosenzweig (1992) point out that “Chapter 11 does not require that a debtor be insolvent in order to qualify for reorganization”. In our sample, 240 of 475 cases (51%) have a higher asset book value than liability book value, which implies that insolvency may not be the only reason for bankruptcy filing in our sample.
18 The U.S. Bankruptcy code section 101 (32A) defines corporate insolvency as an entity that has a “financial condition such that the sum of such entity’s debts is greater than all of such entity’s property, at a fair valuation”. Determining such fair valuation requires in-depth projection of a firm’s long-term performance. In a similar context, the Swedish 1987 Bankruptcy Act defines insolvency as “the debtor cannot pay his debts when due and that this incapacity is not merely temporary.”
viable and economically efficient or viable firms, as Mooradian (1994); White (1994) put it. Because of the timing linked to these two concepts, we expect firms to realize their liquidity states earlier than their insolvency states. In our model, information is essential for determining whether a firm is subject to insolvency or illiquidity in bankruptcy. Once a firm enters the reorganization process, if it cannot solve its short-term debt serving issue by restructuring or refinancing, it will fail to emerge from bankruptcy. Information about whether a firm can survive such liquidity shocks can be observable in a short horizon. What is more challenging is deciding whether a firm is solvent since it requires forecasting future cash flows. Financial information can improve the accuracy of future cash flows prediction and, consequently, a firm’s long-term value. Such forecasting improvement can ultimately lead to an efficiency improvement in bankruptcy decisions. To be consistent with the previous literatures discussing the efficiency of Chapter 11, we consider Chapter 11 to be efficient if it preserves solvent firms and eliminates insolvent firms. In this spirit, information can provide better forecast of a firm’s long-term value and improve Chapter 11 efficiency, ceteris paribus.

1.3.2 Baseline Model

This section proposes a three-period model in which firms sequentially experience liquidity shocks and solvency shocks. The key difference between traditional reorganization and prepackaged reorganization lies in the timing of firms’ emergence. Firms under prepack emerge right after their liquidity shocks is realized, whereas firms under traditional bankruptcy choose to spend more time and costs to generate a noisy signal about their solvency conditions. Therefore, the choice between prepack and traditional bankruptcy is determined by the trade-off between the extra cost in traditional bankruptcy and the benefits of the signal it generates. Firms are more likely to choose prepack given noisier signals and lower downside risk. Because prepack firms emerge regardless of their solvency condition, they tend to have a higher
emergence rate than traditional bankruptcy. Conversely, traditional bankruptcy would successfully filter some inefficient firms from efficient firms, and the overall refiling rate would be lower than that for prepack.

Figure 6 illustrates the decision-making process when a financially distressed firm enters bankruptcy. Firm value $A$ is observed at filing. There are three periods in our model. At time 0, the creditor can choose to file either pre-packaged or traditional reorganization. The cost of prepack is $c_p$, and the cost of traditional Chapter 11 is $c_T$. Firms can liquidate at a cost $c_L$ if they fail to emerge or are found insolvent and refile later. We assume that the costs of the three bankruptcy procedures satisfy the following condition: $c_L > c_T > c_p$. The previous literature shows that prepack has a shorter duration as well as lower direct costs and indirect costs compared to traditional Chapter 11. The direct costs include legal, administrative and advisory fees incurred during the bankruptcy procedure. The indirect costs in bankruptcy are mostly time related, and they can include foregone growth; additional operating costs, including reduced demand and increased production costs raised by distrustful employees, suppliers and customers (bargaining inefficiency); the fire sale liquidation of assets; and time spent by management on restructuring rather than operating activities (Acharya, Bharath, & Srinivasan, 2007; Betker, 1995; Bris et al., 2006; Wruck, 1990). In general, we can safely assume the total costs of prepack are lower than those of traditional Chapter 11.$^{19}$

In the baseline model, we assume all firm owners behave collectively in decision making; thus, we can treat the decision-making problem as a representative owner’s choice between reorganization processes based on her expected utility of the outcomes. We further assume that

$^{19}$ However, Wruck (1990) notes that longer time spent in bankruptcy is not necessarily bad if firms engage in value-enhancing activities, such as productive restructuring and strategic changes, during the procedure. Betker (1995) finds that the direct costs of prepack are comparable to those of traditional Chapter 11 if pre-bankruptcy expenses are included. Although these findings may weaken this assumption, we believe it still holds in general since other time-related indirect costs are not captured in those studies.
the owner is risk neutral, where the utility function is \( U(x) = x \). Then, the choice of reorganization process would be based on her expected value at time 0.

[Insert Figure 6]

With regard to the liquidity and solvency state, we treat them as realizing cash flows at different times. In period 1, cash flow \( R_1 \) is realized, which represents the firm’s liquidity state. There are two possible states: good and bad, i.e. \( R_1 \in \{ R_1^g, R_1^b \} \). The probability of having a good state in period 1 is \( q \). If \( R_1^b \) is realized, the firm cannot meet its liquidity constraint and would fail to emerge from reorganization. Subsequently, it would be liquidated at a cost of \( c_L \). If \( R_1^g \) is realized, a firm meets its liquidity constraint. Prepack firms would emerge at a cost of \( c_P \) as long as the expected value of emergence exceeds the early liquidation value. In contrast, a firm filing under traditional Chapter 11 would not emerge. In period 3, cash flow \( R_2 \) is realized, which represents the firm’s solvency state. There are two possible states: good and bad, i.e. \( R_2 \in \{ R_2^g, R_2^b \} \). We assume that allowing inefficient firms to emerge from bankruptcy would destroy firms’ value further, i.e., \( R_2^g > 0 > R_2^b \). If \( R_2^b \) is realized, the firm is defined as insolvent. It would then refile bankruptcy and be liquidated in period 3. The probability of having a good state in period 3 is \( p \).

In period 1, prepack firms and traditional Chapter 11 firms receive the same information about the firm’s liquidity state and give the same response. The difference lies in the information acquisition over the firm’s solvency state. In period 2, a noisy \( S \) signal regarding

\(^{20}\) In reality, most refiling cases feature substantial reductions in asset value compared to the asset value when the firm emerged from its last bankruptcy.

\(^{21}\) For simplicity, we assume an exogenous probability of insolvency suggesting that the costs of bankruptcy procedure will not affect the firm’s solvency state. This would be true if the cash flow gap in different solvency states were relatively larger than the costs. Since the bankruptcy cost is 3% on average for traditional chapter 11 and the difference between solvent and insolvent firms is much wider, we believe that this assumption is valid. Otherwise, if the cost of bankruptcy increases the chance of insolvency, traditional chapter 11 will be less attractive, but the trade-off we propose should still hold. One can imagine an even higher cost in this case since the solvency cost is also included.
the firm’s solvency state is released. Firms under traditional bankruptcy would spend a higher cost \(c_T\) to forego early emergence and receive signal \(S \in \{S^g, S^b\}\) before they emerge. Assume that the probability of receiving a good signal \(S^g\) would be the same as the probability that the firm is in a solvent state, which is \(p\). The signal is noisy, which means it has a probability \(\varepsilon\) of being wrong about the good state, i.e., \(p(R_2^b|S^g) = \varepsilon\). When \(\varepsilon = 0\), the signal can perfectly predict the solvency state, whereas when \(\varepsilon > 0\), the signal is noisy. In traditional Chapter 11, the owner would not choose to emerge from traditional Chapter 11 if a bad signal is observed. The firm would only emerge if a good signal is received and the expected value of emergence under a good signal exceeds the early liquidation value.

Next, we can derive the expected firm value under both prepack and traditional bankruptcy.\(^{22}\)

The expected value for firms under prepack is

\[
V_p = (A + R_1^b - c_L)(1 - q) + q[(A + R_1^g - c_p + R_2^g)p + (A + R_1^g - c_p + R_2^b - c_L)(1 - p)]
\]  

(1)

The expected value for firms under traditional Chapter 11 is

\[
V_T = (A + R_1^b - c_L)(1 - q) + (A + R_1^g - c_L)q(1 - p) + qp[(1 - \varepsilon)(A + R_1^g - c_T + R_2^g) + \varepsilon(A + R_1^g - c_T + R_2^b - c_L)]
\]

(2)

Then, we explore the determinants of the choice between prepack and traditional Chapter 11. Here, we define \(\Delta\) as the difference between the expected value of traditional Chapter 11 and the expected value of prepack. When \(\Delta \geq 0\), creditors prefer traditional Chapter 11 over prepack and vice versa. We can derive \(\Delta\) from (1) and (2) and obtain

\[
\Delta = V_T - V_p = q[-(1 - p)R_2^b] - q\varepsilon(c_L + R_2^g) + q\varepsilon R_2^b - q(p c_T - c_p)
\]

(3)

\(^{22}\)See Appendix 1 for the proof.
The first term represents the benefit of signal, which is avoiding bad cash flow realization in period 3. The second term represents the cost of a noisy signal related to the type I error of traditional Chapter 11 (i.e., liquidating efficient firms in period 1). Not only is good cash flow realization in period 3 foregone but also additional liquidation costs occur due to this type I error. The third term represents the cost of a noisy signal related to the type II error of traditional Chapter 11 (i.e., allowing inefficient firms to emerge and fail again in period 3). The last term represents the additional costs of traditional Chapter 11. Traditional Chapter 11 dominates prepack whenever the cash flow benefit outweighs the costs. The choice between the two procedures depends on the costs, which leads to our first hypothesis.

**Hypothesis 1**: Firms prefer prepack over traditional Chapter 11 when the cost of prepack is low and when the costs of traditional Chapter 11 and liquidation are high. Firms prefer prepack to traditional Chapter 11 when the noisiness of the signal is high in traditional Chapter 11, i.e., a high $\varepsilon$, and when their downside risk is low, i.e. a high $p$.

To derive the hypothesis, we need to take the first-order derivatives of equation (3) with respect to $c_L, c_T, c_P$. The interesting result here is that higher liquidation costs induce firms to favor prepack because of the noisy signal associated with traditional Chapter 11. Under traditional Chapter 11, a proportion of $q(1-p)$ firms are liquidated at time 2 after receiving a bad signal. An additional $pq\varepsilon$ portion will then be liquidated at time 3. On the other hand, only $q(1-p)$ firms under prepack are liquidated in period 3. Hence, a higher liquidation rate under traditional Chapter 11 leads to a negative relationship between filing traditional Chapter 11 and liquidation costs.

The key element that we introduce in this model is the signal received in traditional Chapter 11. The noisiness of the signal plays an essential role in the choice between prepack and traditional Chapter 11. Taking the first-order derivative of equation (3) with regard to $\varepsilon$, we can find that $\Delta$ and $\varepsilon$ are negatively correlated. For noisier signals, traditional Chapter 11
would allow more inefficient firms to emerge (type II) and more efficient firms liquidate at time 1 (type I). The increasing occurrence of both type I and type II errors reduces the value of signal in two manners. Fewer efficient firms emerge, thus reducing the cash flow benefit in traditional Chapter 11. Meanwhile, the increasing number of emerging inefficient firms drives up the total liquidation costs from future refiling. This would eventually lead to favorability towards prepack rather than traditional Chapter 11.

For a given firm, the probability of good state \( p \) (defined as solvency risk) is known beforehand. For different firms \( i \), their future value could differ. Our model also elucidates the quality level of firms that choose prepack. By taking first-order derivatives on function (3) over \( p \), we determine that the relationship between \( \Delta \) and \( p \) is negative. The major reason that firms choose traditional Chapter 11 is that by using the signal, inefficient firms can be effectively filtered from efficient firms and avoid cash flows losses. Firms are less concerned about such losses when the downside risk is low. Therefore, we expect firms with higher ex ante quality to choose prepack.

**Hypothesis 2**: Firms undergoing prepack have a higher emergence rate and higher refiling rate than those undergoing traditional Chapter 11.

The model predicts some noticeable bankruptcy outcome differences between prepack and traditional Chapter 11. First, the emerging ratio should be lower in traditional Chapter 11 because it liquidates some liquid firms based on the projection that they will be insolvent in the future. Second, both the prior and posterior refiling rate would be lower for traditional Chapter 11 because more economically nonviable firms are filtered out. Table 2 illustrates the theoretical probability of outcomes from our mode.

[Insert Table 2]
1.3.3 Bargaining Power and Conflicts

In the baseline model, it is assumed that all creditors agree about the bankruptcy choice; thus, we treat the decision-making problem as a representative owner’s choice. In this section, we relax this assumption and introduce two types of claimholders of the firm: senior creditors and junior creditors\(^{23}\). Both creditors hold homogeneous beliefs about the distribution of firm value. Intuitively, senior creditors have priority in claims against the firm. Here, we assume absolute priority for senior claims, such that junior creditors will receive nothing unless the senior creditors’ claims are fully satisfied\(^{24}\). Denote the senior claim amount as \(S\) and the expected firm value as \(V\). Thus, the senior creditors’ payoff will be \(V_{\text{Senior}} = \min(S, V)\), and the junior creditors’ payoff will be \(V_{\text{Junior}} = V - \min(S, V) = \max(0, V - S)\). Then, we explore two types of creditors’ decision making separately. We find that creditors disagree about the choice between prepack and traditional Chapter 11 when the senior creditors hold a moderate level of the total claims. For example, when \(S \in (A + R_1^g - c_T + R_2^b - c_L, A + R_1^g - c_p + R_2^b - c_L)\), senior creditors strictly prefer prepack since they can fully recover in prepack, whereas traditional Chapter 11 risks the loss of some of their claim. This is regardless of firm’s preference. Hence, if the firm prefers traditional Chapter 11, which means junior creditors would prefer traditional Chapter 11, conflicts will arise. For other cases, such as when \(S \in (A + R_1^g + R_2^g - c_p, A + R_1^g - c_L)\), junior creditors would strictly prefer prepack since they disproportionally enjoy the cost saving feature of prepack. Conflicts arise in the cases in which the firm prefers traditional Chapter 11.

**Hypothesis 3:** Conflicts regarding bankruptcy choice can arise when a group of creditors have different seniorities for their claims. However, in the case of homogeneous beliefs,

\(^{23}\) A similar setting is used in Bolton and Oehmke (2015), who explore the role of derivatives in bankruptcy.

\(^{24}\) This assumption is generally referred to as the “Absolute Priority Rule” in Chapter 11. In reality, this assumption may not always hold (Bris et al., 2006; Weiss, 1990). We will discuss this topic in the later part of this section.

\(^{25}\) Note: the sizes of claims are commonly used as an indicator of bargaining power.
conflicts can be resolved through wealth transfer mechanisms and the overall reorganization choice and welfare is unchanged\textsuperscript{26}.

Intuitively, when $S$ is too small, senior creditors will fully recover their claims regardless of the bankruptcy procedures. Therefore, senior creditors are indifferent about the choice between prepack and traditional Chapter 11. Meanwhile, the surplus from choosing prepack (or traditional Chapter 11) all goes to the junior creditors. Thus, the junior creditors’ preference is consistent with the firm’s preference, as in the representative-creditor setting, and no conflicts will occur. In an extreme scenario, $S = 0$, which is identical to the representative-creditor model. When $S$ is too large, the junior creditors will receive nothing regardless of the bankruptcy procedures. The senior creditors receive all of the residual firm value and act as a representative creditor, which makes the situation identical to the baseline model. No conflicts will arise in this situation. However, when senior creditors hold a moderate level of the total claims, conflicts may arise. The reason is that the junior creditor holds the residual claims of the firm. Conflicts occur when the cost and the surplus associated with the traditional Chapter 11 are disproportionally distributed between two groups of creditors.

However, even in the presence of conflicts, the group decision can be identical to that in the representative-creditor model. We define surplus $S^i$ (or deficit if negative) by choosing traditional Chapter 11 over prepack for junior creditors and senior creditors separately regarding different senior claim $S$. $S^i = V^i_t - V^i_p$ and $i \in \{\text{junior, senior}\}$. When both surpluses are positive, both creditors agree to choose traditional Chapter 11. Disagreement arises when one is positive and the other is negative. However, the senior creditors can compensate the junior creditors so they are indifferent about choosing prepack or traditional Chapter 11. Meanwhile, the senior creditors can still enjoy a surplus equal to firm surplus $|\Delta|$.

\textsuperscript{26} See Appendix 2.1 for the proof.
This strategy will always be valid under the homogeneous beliefs assumption\textsuperscript{27}. Thus, even with disagreement between parties, the choice will be identical to that in the representative-creditor model. Therefore, bargaining power does not change the choice between prepack and traditional Chapter 11. In addition, we can see that a violation of the APR can arise since the compensation to the junior creditors is guaranteed ex ante. Even if the realized firm value is not sufficient to cover the senior creditors’ claim (i.e., the senior creditors are not fully recovered), the junior creditor can still receive something, which can be observed as a violation of the APR.

1.3.4 Debt-Equity Conflicts

A special version of this two decision makers setting can be used to study debt-equity holder conflicts. Equity holders are junior claimholders, having limited liability and making final bankruptcy decisions. Debt-Equity conflicts can arise when both parties disagree on the best bankruptcy choice. When equity holder’s interests are aligned with the firm’s best interests, equity holder’s decisions are optimal. However, when equity holder’s interests are against firm’s interests, equity holders can be motivated to choose a bankruptcy process in their own favor at the cost of the debt holders and the total firm value. For instance, when $S_{\text{firm}} < 0$, $S_{\text{equity}} > 0$ and $S_{\text{debt}} < 0$, equity holders prefer traditional Chapter 11, while prepack is optimal for debt holders and firms. Nevertheless, equity holders can decide to choose traditional Chapter 11 to free ride debt holder’s information acquisition costs since they are protected by limited liability\textsuperscript{28}. In addition, equity holders can demand rent from debt holders during bargaining. However, their ability to do so is constrained under the supervision of bankruptcy court. For instance, cramdown allows the bankruptcy decision to be in favor of the

\textsuperscript{27} In the case of heterogeneous beliefs, two additional features could arise. First, creditors may disagree on the wealth transfer compensation amount. Second, certain creditors can willingly transfer a large amount of wealth to the others, leading to a suboptimal group decision when there are large deviations in beliefs.

\textsuperscript{28} I owe my thanks to Tak-Yuen Wong for suggesting this interpretation.
creditors when the court detects any wrongdoing or unreasonable demands from the equity class. We assume two scenarios for cramdown: (1) bankruptcy procedure: court has a probability of $\mu$ to cramdown when equity holders are not acting in the best interests of the firm, and (2) deviation from APR: court has a probability of $f(x)$ to cramdown when equity holders demand a fraction $x$ of the debtholder’s surplus. $f(x)$ is an increasing function of $x$.

This model is generalized when no supervision is achieved when the cramdown probability ($\mu$ in (1) and $f(x)$ in (2)) is always 0 and full supervision is achieved when the cramdown probability is always 1. As we show in hypothesis 4, a court focusing on the right bankruptcy procedure can always achieve a socially optimal bankruptcy choice while it is not always true for a court focusing on deviation from APR. Overall, the court’s ability to cramdown equity holders’ wrongdoing is negatively associated with how much rent equity holders can extract.

**Hypothesis 4**: When a court focuses on the right bankruptcy procedure, both parties will agree on a mutually beneficial wealth transfer $x$, such that $1 - \mu > x > (1 - \mu) \frac{-S_{\text{Junior}}}{S_{\text{Senior}}}$, which will always exist. When a court focuses on deviation from APR, both parties will only agree on a mutually beneficial wealth transfer $x$, such that $(1 - f(x)) x S_{\text{Senior}} + S_{\text{Junior}} > 0$. Such $x$ only exists when $\max_x [(1 - f(x)) x S_{\text{Senior}} + S_{\text{Junior}}] > 0$, which will not always hold\(^{29}\).

Intuitively, when the court focuses on the right bankruptcy procedure, equity holders are incentivized to make the right decision and not punished by taking too much rent from debt holders for altering their initial decision. Therefore, they are more likely to make the right decision. However, when the court focuses on deviation from APR, equity holders are punished from demanding too much rent if they choose the optimal decision. Therefore, they would

\(^{29}\) See Appendix 2.2 for the proof.
strictly prefer the suboptimal decision where no cramdown occurs since they do not demand any rent.

1.4 Data

In this paper, we utilize data to analyze the difference between pre-packaged Chapter 11 and traditional Chapter 11. The primary data we use come from the UCLA-LoPucki Bankruptcy Research Database (BRD), and the original dataset contains 998 bankruptcy cases from 1980 to 2014. All firms filed an annual report (Form 10-K) with the SEC, for a year ending not less than three years prior to the filing of the bankruptcy case and had assets worth $100 million or more, measured in 1980 dollars, as of the last 10-K filed prior to bankruptcy. We drop 3 cases because they are dismissed before the order of relief and another drop 36 cases whose emergence status we cannot determine. This leaves 959 cases in the sample, with 679 traditional Chapter 11 cases and 280 pre-packaged or pre-negotiated Chapter 11 cases. Overall, 660 firms emerged from bankruptcy, and 140 firms refiled after they emerged. Among the 679 traditional Chapter 11 cases, 264 cases (39%) did not emerge from Chapter 11, and 84 (12%) refiled for bankruptcy within 5 years after their emergence. Among the 280 pre-packaged Chapter 11 cases, 56 cases (13%) did not emerge from Chapter 11, and 39 (20%) refiled for bankruptcy within 5 years after their emergence. The results still hold if we examine industry-specific subsamples\textsuperscript{30}. Overall, we observe there is a higher emergence rate and refiling rate for prepack.

We then use Compustat data and CRSP data to complete the firms’ pre-bankruptcy and post-bankruptcy financial information. Table 1 summarizes the financial data and key variables for both pre-packaged Chapter 11 and traditional Chapter 11 cases. By just looking at the statistical summaries, we can observe that the post-bankruptcy firms tend to have lower leverage, higher

\textsuperscript{30} See the Online Appendix for an industry-specific comparison.
liquidity and higher profitability than pre-bankruptcy firms. This is observed in both pre-packaged Chapter 11 and traditional Chapter 11. Nevertheless, noticeably, the profitability increase is much smaller in prepack than traditional Chapter 11. There are two possible explanations for this observation. First, the bankruptcy procedure significantly improves the financial status of firms through reorganization. However, restructuring does not seem to bring a direct benefit for pre-packaged Chapter 11. Alternatively, we can explain this as survival bias; that is, firms that survive the bankruptcy procedure are in a stronger position than those that do not emerge. Thus, bankruptcy functions as a filtering process with certain costs.

To study the impact of the bankruptcy process on firms’ post-bankruptcy performance, we require firms to have at least a 5-year interval after they emerge from bankruptcy to ensure that their refiles within 5 years are representative. This requirement narrows the emerging firm sample down to 504 cases and 89 representative refiling cases. We also hand-collect claim information for 245 public firms that had disclosure statements or plans of reorganization available in the SEC’s EDGAR system from 1994 to 2017 and use this information to construct a bargaining power index at the firm level in next section.

Our theory suggests information acquisition is the key element that distinguishes traditional Chapter 11 from prepack. To empirically test that, we use RavenPack data to identify the amount of bankruptcy-specific news exists around a firm’s bankruptcy period. The RavenPack news database provides a comprehensive sample of firm-specific news stories from the Dow Jones News Wire (See, e.g., Kelley and Tetlock (2017) and Ben-Rephael, Da, and Israelsen (2017) for recent studies using this dataset). We manually match the RavenPack database with our sample through both current firm names and historical firm names. To capture a news story specifically about a firm’s bankruptcy-related information, we choose group type “Bankruptcy”

31 Company filings from the EDGAR system are available starting in 1994.
provided by RavenPack. Every news item has a “relevance score”, which ranges from 0 to 100, capturing how closely the underlying news applies to a particular company, with a score of 0 (100) meaning that the entity is passively (predominantly) mentioned. All news entries in our sample have a “relevance score” of 100. We also check the “event novelty score” (ENS) provided by RavenPack, and the mean ENS of our sample is approximately 70, which indicates most of the information revealed through the news entries are fresh news. We choose the bankruptcy news sample period to be from 6 months before a firm’s bankruptcy filing to 1 year after the firm emerges\textsuperscript{32}. We count the number of bankruptcy news entries during the firm’s bankruptcy period and use it as a key variable to analyze the role of information in bankruptcy results.

### 1.5 Empirical Test

Next, we will empirically test the hypotheses that we developed to address the refiling puzzle. An efficient Chapter 11 process should be able to distinguish economically viable firms from nonviable firms (White, 1994). Economically nonviable firms may emerge from Chapter 11 because the inefficiency filtering process fails to identify those firms and liquidate them. Later, when their true state is realized, those firms would suffer from insolvency and file for bankruptcy again. Therefore, one key ex-post proxy that reflects such efficiency should be emerging firms’ refiling rate.

The first part of this section will further establish the differences in refiling rates between traditional Chapter 11 and prepacks. We find consistent evidence supporting that prepack is associated with a higher refiling rate. There are two potential explanations for this phenomenon. Traditional Chapter 11 may be more efficient in filtering bad firms from good ones, and fewer nonviable firms may therefore emerge from traditional Chapter 11, which creates a better

\textsuperscript{32} We also choose news items strictly from firms’ bankruptcy filings until they emerged. Our results are still robust.
pooling of firms and less bankruptcy post-bankruptcy. An alternative explanation may be that high-risk firms optimally choose prepack as their bankruptcy process ex ante to benefit from its low costs and to preempt liquidation (Eckbo & Thorburn, 2008), which could explain why their ex-post refiling rate is so high since they are simply riskier than firms filing under traditional Chapter 11. This explanation does not undermine the socially undesirable nature of using prepack because it allows risky firms to survive through bankruptcy. However, we can also not reach the conclusion that traditional Chapter 11 is more efficient in filtering, as the refiling difference is explained by the ex ante risk profile rather than what is occurring within the bankruptcy process. Moreover, if the refiling difference purely comes from the ex ante risk profile, a lower emergence rate in traditional Chapter 11 indicates its inability to allow good firms to reorganize. Previously, we showed that the means/medians of the various pre-bankruptcy characteristics indicate that prepack firms are not riskier ex ante.

To test these two hypotheses formally, we further apply various econometric methods in this section. First, in our regressions, we control for firms’ risk profile variables, including size, leverage, liquidity, profitability and investment. Second, we perform a two-stage least square regression to further address self-selection and omitted variables issues related to prepack. Finally, we structure a post-emergence panel dataset to perform a cox-hazard regression in order to capture time-varying features. We find that the results are robust after we control for risk profiles. Therefore, the empirical evidence supports the filtering hypothesis rather than the risky firm hypothesis.

The second part of our empirical analysis focuses on how prepacks and traditional Chapter 11 differently affect the bankruptcy emergence rate. This examination is a key part of explaining the refiling puzzle we observed earlier. We find that traditional Chapter 11 is associated with a lower emergence rate, which supports the filtering hypothesis in explaining the lower refiling rate. However, it does not necessarily rule out the downside that Chapter 11
may also eliminate more good firms in the process. If one bankruptcy process has a lower emergence rate but a higher refiling rate, it must be inefficient, as it not only allows fewer good firms to emerge from bankruptcy (higher type I errors) but also actually allows more bad firms to survive (higher type II errors). In contrast, a low refiling rate ex-post suggests that the process is efficient in filtering bad firms.

A lower emergence rate can result from fewer good firms, fewer bad firms or a mixture of both emerging from bankruptcy. It is empirically impossible to directly determine whether traditional Chapter 11 preserves more good firms because once firms are liquidated, their true solvency states are unobservable. Instead, this paper applies an indirect method by establishing the fact that traditional Chapter 11 firms have worse pre-bankruptcy characteristics and lower post-bankruptcy refiling rates. This observation implies that traditional Chapter 11 preserves a higher proportion of good firms than prepack through a tougher filtering scheme. Ideally, we want a system to have a high emergence rate and low refiling rate to efficiently filter bad firms from good firms. However, in reality, due to frictions such as imperfect information and costly information acquisition, having fewer bad firms post-bankruptcy comes at a cost of simultaneously having fewer good firms.

In the last part of this section, we examine the determinants of the choice between prepack and traditional Chapter 11. Consistent with our model predictions, we find that firms with noisier signals and lower downside risk prefer prepack.

1.5.1 Refiling

The framework of the legal process is important in determining its outcomes. Table 3 uses logistic regression to explore the relationship between refiling for bankruptcy among emerging firms and the choice of Chapter 11. In columns (1) to (5), we examine the relationship between prepack and refiling within a 5-year window post-bankruptcy.
We use refiling within 5 years as our dependent variable rather than lifetime refiling for three reasons: First, the lifetime refiling variable underestimates the number of refiles for recent bankruptcy cases. Most recently emerging cases may not have had sufficient time to realize their economic viability even though they may refile very soon. Such underestimation bias worsens towards prepacks considering the fact that the number of prepacks has increased significantly in the past few years. Second, exogenous shocks independent of bankruptcy procedure may affect the refiling rate if the refiling occurs decades after a firm’s emergence from bankruptcy, which sabotages the purpose of our analysis. Third, lifetime refiling may not well present the refiling probability in a cross-sectional sample because firms can be at different stages after bankruptcy: one may have recently emerged from bankruptcy, while others may file thirty years later. Refiling would have different causes for these two firms. Therefore, we choose refiling within 5 years as a more consistent measure for our cross-sectional data.

To control for firm characteristics and risk profile, we add firm size, leverage, liquidity, profitability and investment to the model. In columns (1) and (2), we separately control for these characteristics at the time of filing for bankruptcy and at the time of emerging from bankruptcy. The increase in R-square from column (1) to column (2) is consistent with the fact that the financial variables at emergence are more relevant to firms’ financial distress than those at the moment of filing for bankruptcy. In column (3), we control for firm characteristics both at the time of filing for bankruptcy and at the time of emerging from bankruptcy. In addition to these variables, we control for the intangible ratio in columns (1) to (4), as measured by intangible assets divided by total assets. We use this measure to proxy for the valuation uncertainty, as in Kumar (2009). Note here that the valuation uncertainty merely reflects the uncertainty in the information rather than the uncertainty in the underlying assets (i.e., risk).

33 We repeat the regression in columns (1) to (3) by changing the dependent variable to lifetime refiling. The results remain robust, although the significance is much lower because of the reasons mentioned above. The r-squares also drop compared to column (1) to (3).
Therefore, we observe a nonsignificant relationship between the intangible ratio and short- to medium-term bankruptcy risk.

Nevertheless, we find a statistically significant and positive relationship between firms’ going through prepack and firms’ refiling bankruptcy in the next 5 years. The result in column (3) suggests that pre-packaged Chapter 11 bankruptcy increases emerging firms’ odds of refiling by 3.30. In column (4), we repeat the regression without prepack. By comparing the R-square value in columns (3) and (4), the choice of prepack alone contributes 25% of the explanatory power in model (3). These results suggest that traditional Chapter 11 bankruptcy has a higher post-bankruptcy survival rate. Additionally, Dahiya et al. (2003) find that DIP financing increases the likelihood that a firm emerges from bankruptcy. In column (5), we added DIP financing into the regression and find that it is positively associated with refiling within 5 years. This finding suggests that DIP financing is related to inefficient filtering because we also find that it is positively associated with a higher emergence rate in a later section. Overall, the results in Table 3 suggest that pre-packaged Chapter 11 is associated with a lower surviving rate, which is consistent with hypothesis 2 regarding our inefficient filtering theorem.

Given the higher refiling rate and higher quality pre-bankruptcy associated with prepack, it is reasonable to expect that something during the bankruptcy process drives this result. Despite our inefficient filtering theorem, one alternative explanation could be that prepack destroys more value during the reorganization process than traditional Chapter 11. This conjecture is highly unlikely for two reasons. First, as previously shown in the literature, prepack is much shorter and less expensive than traditional Chapter 11, and the idea that a shorter and cheaper process destroys more values is counterintuitive. Second, Kalay et al. (2007) show that prepack is empirically irrelevant to the excess operating income of the firm during the bankruptcy process.

[Insert Table 3]
1.5.1.1 Instrumental Variable

Nevertheless, bankruptcy is a comprehensive procedure, and there may be omitted variables overlooked in our model. If prepack firms are riskier ex ante based on an unobserved characteristic, this characteristic may explain the high refiling rate, which could lead to an endogeneity issue when firms that are more likely to refile post-bankruptcy ex ante choose prepack.

To reduce endogeneity concerns, we perform a two-stage least square regression using an instrumental variable approach in Table 4. Previous literature (McConnell & Servaes, 1991) suggests that firms with simpler capital structure are more likely to file pre-packaged Chapter 11 bankruptcy. Here, we introduce the number of files in the bankruptcy court docket for a bankruptcy case at the time of confirmation as an instrumental variable.

To justify this variable as a strong instrumental variable in our analysis, two criteria are essential: the inclusion criterion requires that the docket number affect the choice of prepack, and the exclusion criterion requires that the docket number not affect the result of refiling after bankruptcy.

The docket number represents the complexity of the case. A complex case would involve a large number of files in the docket because of a diverse group of claimholders, strong conflicts in bankruptcy or complex claim structures, all of which are easy to anticipate by creditors pre-bankruptcy. A diverse group of claimholders would make it more difficult to reach consensus on the reorganization plan before filing and require more document filings during bankruptcy. For instance, Ivashina et al. (2016) find that creditor concentration is positively related to prepack filing. Meanwhile, complex claim structures may involve contracts such as executory contracts, which are treated favorably in non-bankruptcy law. An executory contract requires that some actions remain on both sides of the contract. Common types of executory contracts
include unexpired lease, development contracts and intellectual property licenses. A bankruptcy trustee may reject such claims under the court’s approval in the Chapter 11 process, lower their bargaining power by transferring these into general unsecured claims and avoid penalties that may otherwise occur in non-bankruptcy law framework. Therefore, large executory contract claims create a disincentive for pre-agreement settlement before filing. During the bankruptcy procedure, the motions to assume or reject any executory contract would likewise increase the number of files. In addition, Chatterjee et al. (1996) find that the nature and complexity of debt claims can determine the firm’s reorganization choice. Overall, the complexity of the case would influence the choice of pre-packaged Chapter 11 bankruptcy, and file numbers can be a good proxy for this purpose.

On the other hand, the exclusion criterion is satisfied since it seems difficult to identify any economic argument suggesting that the complexity of the bankruptcy case would influence the future financial distress of the emerged firm. One may argue that a more complex case incurs more costs, which decreases the firm value post-bankruptcy. To address this concern, we also repeated the analysis including direct costs. Our results remain robust.

[Insert Table 4]

In addition, we perform a range of diagnostic tests to ensure that our instrument is sufficiently strong to identify prepack. For our 2SLS model, we perform the following tests: (1) an under-identification test (Kleibergen & Paap, 2006); and (2) a weak instruments test (Kleibergen & Paap, 2006; Stock & Yogo, 2005). In all cases, we conclude that our instruments are valid. For our 2SLS model, we (1) reject the null that our matrix of reduced form coefficients is under-identified (Kleibergen-Paap rk LM statistic = 51.65, p-value = 0.00); and (2) reject the null that our first-stage equation is weakly identified (Kleibergen-Paap Wald rk F statistic = 334.38, which is higher than all of the Stock-Yogo weak instrument test critical values, ranging from 5.53 to 16.38).
Column (1) in Table 4 shows the first-stage regression result. The negative sign on number of docket files suggests that a distressed firm is less likely to file a pre-packaged Chapter 11 bankruptcy if the case is complex, as the previous literature suggests. Column (2) in Table 4 represents the second-stage regression, showing that pre-packaged Chapter 11 bankruptcy would increase the likelihood of refiling.

1.5.1.2 Cox-hazard Regression

All previous analyses are based on firms’ cross-sectional information. While the evidence supporting our hypothesis is strong, time-varying factors after the bankruptcy may play an important role in firms’ refiling, and our previous analysis overlooked these factors. For example, consistent overinvestment/underinvestment for prepack firms after their emergence may ultimately lead to higher refiling rates. Therefore, we combine our sample data with Compustat data and construct a panel data from the firms’ emergence to their refiling or the end of sample period on December 31, 2014, whichever comes earlier. Sixteen firms refiled twice in our sample. For technical results, we exclude their second refile (third-time bankruptcy), which enables us to use the single failure cox-hazard model to analyze the results. In column (1) of Table 5, we find that pre-packaged Chapter 11 bankruptcy increases the hazard ratio of refiling to 3.68 after we control for financial variables, industry fixed effects and year fixed effects. In column (2) of Table 5, we use the GDP instead of year fixed effects and find similar results. The negative relationship between GDP and refiling indicates a positive correlation between the aggregate economic distresses and firms’ financial distress. Firms are more likely to suffer financial distress in economic downturns when overall liquidity in the market is low, demand is low and financing cost increases, and vice versa. With regard to financial variables, we find that profitability and investment are the most important indicators of a firm’s financial distress. Post-bankruptcy firms can reduce their refiling rate by increasing investment, which indicates that under-investment is common among those firms.
1.5.2 Emergence

In this section, we examine the relationship between a firm’s choice of Chapter 11 and its emergence rate during bankruptcy. Table 6 shows the result of logistic regressions for the determinants of firm emergence from Chapter 11 bankruptcy. We control for firms’ characteristics at refiling as well as their intangible ratio in column (1). The results in column (1) suggest that pre-packaged Chapter 11 bankruptcy increases firms’ odds of emergence by 4.18. In column (2), prepack is dropped. A comparison of columns (1) and (2) shows that the R-square increases from 0.0437 to 0.0787, which indicates that the choice of prepack or pre-negotiation contributes 44% of the explanatory power in comparison with the rest of the control variables. In column (3), an interaction term between prepack and intangible ratio is introduced. In column (4), we add an indicator variable of DIP financing. Consistent with Dahiya et al. (2003), the result show that DIP does increase the likelihood of emergence. However, this result does not change the robustness of our results for prepack. Interestingly, DIP also increases refiling, as we previously showed, which could suggest that DIP financing is associated with inefficient filtering in Chapter 11.

There are two potential explanations for why prepack increases the emergence rate. One reason could be that pre-packaged Chapter 11 bankruptcy is cost efficient, allowing more firms to emerge from bankruptcy. An alternative justification is that pre-packaged Chapter 11 bankruptcy is less efficient in filtering inefficient firms from efficient firms through the bankruptcy procedure. If the previous explanation holds, and if the filtering efficiencies are assumed to be identical for both processes, we should expect firms emerging from pre-packaged Chapter 11 bankruptcy to suffer less financial distress post-bankruptcy because of their cost saving. In contrast, if the opposite is true, it would support our hypothesis that prepack
is less efficient in filtering. Empirical evidence in the previous section supports the latter explanation.

[Insert Table 6]

1.5.3 Role of Information

After examining the impact of pre-packaged Chapter 11 bankruptcy on refiling and emergence, Table 7 illustrates what governs the choice of pre-packaged Chapter 11 bankruptcy using logistic regressions. Previous studies show that intangible assets are related to valuation uncertainty (Edmans, 2011; Kumar, 2009) and that neither market nor managers can accurately evaluate those investments (Lev, 2004). In addition, it is empirically unrelated to firms’ risk profiles because in Table 3, we do not see a statistically significant positive relationship between intangible assets and refiling. Thus, we use the intangible ratio as a proxy for the noisiness of the signal that firms would receive during traditional Chapter 11. We find that firms with high intangible assets tend to choose pre-packaged Chapter 11 bankruptcy over traditional Chapter 11. Column (1) shows that increasing the intangible assets ratio by one percentage point would increase the likelihood to file under pre-packaged Chapter 11 bankruptcy by 5.6% after we control for firm characteristics, year fixed effects and industry fixed effects. In column (2), we drop intangible assets. By comparing R-squares in column (1) and column (2), we find that intangible assets contribute 52% of the explanatory power for the choice of pre-packaged Chapter 11. This empirical finding supports hypothesis 2 in our model. Intangible assets increase the noisiness of the signal and make traditional Chapter 11 bankruptcy’s signal less favorable.

At first glance, this result is consistent with that of Eckbo and Thorburn (2008). However, their explanation is that firms with higher intangible assets are more sensitive to fire sales. An alternative explanation for this relationship could be that firms with higher intangible assets
are more likely to file prepack because they are motivated to preempt liquidation. To test this hypothesis, we include industry-specific assets as defined in (Eckbo & Thorburn, 2008) in column (3). Industry-specific asset is the book value of the property plant and equipment as a proportion of the firm’s total assets last reported. Firms with higher industry-specific assets are more subject to fire sales discount (Williamson, 1988). If the preempt liquidation hypothesis is true, we should expect a positive relationship between specific assets and prepack; however, this is not the case. Thus, the liquidation pre-emption hypothesis may not hold in the U.S. pre-packaged Chapter 11 scenario. Moreover, (Eckbo & Thorburn, 2008) proxy intangibles as unsecured debt/total debt, which may capture the concept of unsecured bargaining power rather than the intangible assets itself. This paper directly uses intangible assets as a percentage of total assets, which better represents intangible assets.

In addition, our results contradict the bargaining power explanation. Previous studies (Bergman & Callen, 1991; Hackbarth et al., 2015) suggest that higher tangibility decreases shareholder bargaining power. Thus, a higher intangible ratio leads to a higher bargaining power for shareholders. An increasing preference towards prepack may be due to shareholders’ preference of prepack. However, this is unlikely for two reasons. First, previous literature has shown that shareholders roles have become trivial in Chapter 11. Second, shareholders may not always prefer prepack even if they are the residual class, especially when creditors hold a relatively small portion of the firm and bear most of the downside risk. Empirically, specific assets do not increase prepack, which rules out this explanation.

[Insert Table 7]

In column (4), we regress prepack on firms’ financial distress levels measured by Altman’s Z-score, and we find that the decision of prepack is positively associated with a higher Z-score. The explanation for this result is that the value of the signal obtained from traditional Chapter
11 diminishes when firms have less downside risk. Therefore, firms under less financial stress would prefer pre-packaged Chapter 11. This result is consistent with hypothesis 3 in the model.

Next, we test the direct relationship between the choice of prepack and bargaining power. We structure the bargaining power at the firm level as $B_i$.

$$B_i = \log\left(\frac{\text{secured claims}_i}{\text{unsecured claims}_i}\right)$$

The benefit of this structure is that it presents the relative bargaining power within the firm. If $\text{secured claims} = \text{unsecured claims}$, $B_i = 0$. When one party holds more claims, $B_i$ becomes positive. Moreover, when the difference is large, $B_i$ is also large. This structure nicely captures the concept of bargaining power imbalance within a firm and potentially through a decision-making process. In columns (5) and (6), we run logit regression of prepack on bargaining power by controlling industry-fixed effects and year-fixed effects separately. We find that intangible assets retain significant explanatory power in prepack. Meanwhile, we do not find any significant relationship between bargaining power and prepack decision. This finding is consistent with the previous hypothesis.

[Insert Table 8]

Lastly, we explore the information’s role during bankruptcy and its impact on post-bankruptcy results. To estimate the level of information acquisition during bankruptcy, we use RavenPack data to find the bankruptcy-specific news around the firm’s bankruptcy period. We count the number of bankruptcy news items during the firm’s bankruptcy period and use it as a key variable to analyze the role of information in bankruptcy results. Table 8 illustrates the logistic regression between the firm’s refiling and its bankruptcy-related news, and shows that

---

34 Alternatively, if we drop the absolute value, the term $B_i^2 = \log\left(\frac{\text{secured claims}_i}{\text{unsecured claims}_i}\right)$ would simply illustrate the bargaining power of secured claimholders relative to the unsecured claimholders. The results are robust to this alternative measure.
information plays an important role in bankruptcy results. Column (1) regresses firm’s refiling on prepack, news and their interaction term. Column (2) regresses firm’s refiling within 5 years on prepack, news and their interaction term.

After the introduction of news, prepack negatively (although not always significantly) predicts firm’s refiling. In addition, we find it is the interaction term between prepack and news that positively predicts a higher refiling rate. The explanation of this finding is two-fold. Firstly, it confirms the higher refiling rates we observe in previous sections are information driven. Without information acquisition, prepack incurs less costs, reserves more firm value than traditional Chapter 11 during bankruptcy, and reduces the likelihood of refiling. Secondly, we find information acquisition during prepack is positively associated with firms’ future refiling rate. Since firms with noisy information self-select into prepack in general, acquiring more information is inefficient. In contrast, the relationship between news coverage and the refiling rate is negative in traditional Chapter 11. Noticeably, the R-square of the regression increases dramatically once news are included compared to the benchmark results in Table 3, which further confirms the importance of information for explaining post-bankruptcy performance.

1.6 Robustness Checks

1.6.1 Managerial Controls, Costs and Investment

The bankruptcy reform of 1978 allows managers to stay in their positions, which enables them to manipulate the process to achieve personal benefits at the cost of creditors (Gennaioli & Rossi, 2010). In the absence of manager-creditor conflicts, Thorburn (2000) finds that the Swedish bankruptcy procedure can be efficient. Prior studies (Adler et al., 2013; Becker & Strömberg, 2012; Hackbarth et al., 2015; Wruck, 1990) have suggested that managers play an important role in the restructure process. Becker and Strömberg (2012) suggest that the Delaware court’s Credit Lyonnais ruling in 1991 shaped managers’ fiduciary duties in favor of
creditors near insolvency\textsuperscript{35}. This shift consequently mitigates equity-debtor conflicts and enhances firms’ value. Given this new trend, we consider Chapter 11 bankruptcy as a way for creditors and managers to align interests and seek value maximization via the information acquisition process.

Nevertheless, CEOs face severe compensation losses if they are fired (Eckbo, Thorburn, & Wang, 2016). Incumbent CEOs leaving the executive labor force suffer median losses of $7 million. Therefore, most incumbent CEOs may act on self-interest and destroy the firm’s value through the bankruptcy process (Hotchkiss, 1995). In our data, the CEO turnover rate tends to be lower for prepack (Table 1). A potential explanation could be that financially motivated and better-informed CEOs in bad firms deliberately push for a prepack reorganization to avoid getting fired. Because of information asymmetry, some of these firms survive through the first bankruptcy and refile later. Thus, the difference in the post-bankruptcy survival rate between the two Chapter 11 processes may result from differences in their CEO turnover rates. CEO turnover should be positively associated with refiling. In Column (1) of Table 9, we add CEO turnover and its interaction term with prepack to a logistic regression of refiling within 5 years on prepack, and in Column (2), we add financial variables. The result suggests that CEO turnover plays a trivial role in the survival rate for both pre-packaged and traditional Chapter 11. Prepack remains significantly and positively related to refiling.

[Insert Table 9]

Direct costs are another important issue in the literature of bankruptcy efficiency. Even if a bankruptcy process efficiently filters nonviable firms from viable firms through information acquisition, an overwhelmingly high cost could drive solvent firms into insolvency. Thus,

\textsuperscript{35} Becker and Strömberg (2012) document the Credit Lyonnais (1991) case in comprehensive detail. One particularly important part of the ruling points out “At least where a corporation is operating in the vicinity of insolvency, a board of directors is not merely the agent of the residual risk bearers, but owes its duty to the corporate enterprise.”
higher costs during the bankruptcy may make firms more likely to refile later, which should lead to a negative relationship between costs and refiling. If one bankruptcy process’s cost establishes a non-negative relationship with refiling, such costs may have some positive externality features. The model suggests the latter because such costs contribute to information acquisition and effectively avoid future loss by emerging as a bad firm. Alternatively, the positive externality may come from productive restructuring and strategic changes during bankruptcy (Wruck, 1990). While we cannot completely rule out the value enhancing hypothesis, it does not explain why factors such as financial wellbeing and information noisiness govern the choice between traditional and prepack in previous sections.

In column (3) of Table 9, we add the proportion of professional fees as a percentage of total assets at filing and its interaction term with prepack to the logistic regression and regress refiling within 5 years on prepack. The result illustrates the cost difference between prepack and traditional Chapter 11. Increasing fees for prepack increase the likelihood of refiling because the costs are redundant. However, the negative sign for fees in traditional Chapter 11 indicates that the costs do not increase the refiling rate. This result supports our hypothesis regarding the economic benefits of information acquisition in traditional Chapter 11 associated with these costs, which is absent in prepack.

In addition, the positive relationship in prepack and nonsignificant relationship in traditional Chapter 11 is contrary to the hypothesis of White (1994), which suggests that higher transaction costs of reorganization discourage inefficient firms from mimicking efficient firms in undergoing Chapter 11. If inefficient firms mimic efficient firms and if Chapter 11 filters them through costs, inefficient firms would prefer prepack because, overall, prepack is cheaper. However, in prepack, if transaction costs are high, we should observe a lower refiling rate, as it filters out more inefficient firms. The first point is not true, as we previously have shown that prepack firms have higher ex ante quality. Moreover, our analysis in Table 9 does not support
the latter argument. The conclusion here is that transaction costs do not filter efficient firms merely through the cost difference; rather, it is associated with its positive externality like information acquisition.

Finally, we want to test whether the results are driven by a specific investment pattern in prepack firms both before and after bankruptcy. In column (4) of Table 9, we add the interaction term of prepack with investment 2 years before filing and the interaction term of prepack with investment 1 year after emergence. Neither coefficient of these two variables appears statistically significant. The impact of prepack on refiling is robust after the inclusion.

1.6.2 Fixed Effects and Judicial Controls

This section tests the impact of pre-packaged Chapter 11 bankruptcy on refiling and emergence after we control for judicial variables and industry fixed effects. Another rich body of literature studies how the judicial variables affect the outcomes of bankruptcy (Bris et al., 2006; Chang & Schoar, 2013; Gennaioli & Rossi, 2010; LoPucki, 2005; LoPucki & Whitford, 1991; Morrison, 2007; Ponticelli & Alencar, 2016). If prepack cases tend to be assigned to judges or courts that are relatively less capable of identifying bad firms or less willing to spend a long time in bankruptcy, then this may explain the higher refiling rate after prepack. In this case, judges’ heterogeneous qualities determine the higher refiling rate rather than the prepack itself. In addition, if the representing DIP financing attorneys are more persuasive, they may lead more bad firms to pass the court confirmation through prepack. To test their impacts, we repeat our main results for the refile rate and emergence rate by controlling for the judge dummies, court dummies and attorney dummies. We find that our results robust to the inclusion of these controls.

Additionally, the fire sale effect on liquidity that concerns Shleifer and Vishny (1992) is an important issue for bankruptcy. Industry-wide contagion effects can dry up the liquidity within
an industry and decrease productivity with outside purchases of the distressed assets (Acharya et al., 2007; Hertzel & Officer, 2012; Jorion & Zhang, 2007). A distressed firm may suffer more in a distressed industry. Therefore, the higher refiling rate in prepack could come from an industrial contagion effect if prepack is more concentrated in distressed industries. To address this industry contagion concern, we control for industry and year fixed effects. We find that the impact of pre-packaged Chapter 11 bankruptcy on refiling remains significant. Moreover, Acharya et al. (2007) document that industrial contagion could increase the likelihood that distressed firms emerge. To test this, we control for industry fixed effects for emergence and observe no change in our basic results.

Meanwhile, we do find some interesting results that coincide with those of previous studies. For example, with regard to bankruptcy judges, the odds of refiling bankruptcy for cases initially signed by Delaware Judge Peter J. Walsh are 2.26 times greater than other cases. Meanwhile, the odds of his cases emerging from bankruptcy are 0.71 times greater than other cases’, although this difference is not statistically significant. In addition, the cases initially signed by another Delaware Judge Christopher S. Sontchi are 0.27 times more likely to emerge from bankruptcy as other cases. These findings support previous studies that judges play central roles in bankruptcy outcomes. We also find evidence that some leading DIP attorneys are positively related to a higher refiling rate. However, we do not find any effects of forum shopping on either the refiling or the emergence rate.

1.7 Conclusion

We propose an information acquisition model that formally explores creditors’ choice between prepack and traditional Chapter 11. Because of its shorter duration in bankruptcy, pre-packaged Chapter 11 skips a signal about a firm’s solvency state for a lower cost. This signal is not beneficial when firms have lower downside risk of insolvency or when the obtained signal is too noisy. Our empirical analysis suggests that pre-packaged Chapter 11 is associated
with a higher emergence rate from the bankruptcy process but a lower survival rate post-bankruptcy. The results are robust to the inclusion of during bankruptcy news coverage, investment, bargaining power, industrial contagion, economic downturns, CEO turnover, professional costs, debtor-in-possession (DIP) financing and judicial variables. Consequently, we conclude that traditional Chapter 11 can better serve the economic function of reorganization and filtering inefficient firms from efficient firms.

Meanwhile, we can draw some important implications from this paper. First, lowering the costs of traditional Chapter 11 is extremely valuable for bankrupted firms, as it will benefit those firms who choose traditional Chapter 11. More importantly, a lower information cost will attract more firms to participate in information acquisition and ensure the overall efficiency of reorganization processes. Second, increasing the information quality of the signal emitted during bankruptcy is equally important. To achieve that goal, encouraging more information disclosure both during and before bankruptcy is essential, as it can effectively mitigate the risk that inefficient firms survive, and efficient firms liquidate during the Chapter 11 process.
1.8 References


1.9 Appendix

1.9.1 Appendix 1

Prepack

For prepack, only firms that realize a bad state as $R_1^b$ fail to emerge from bankruptcy. These firms are liquidated at a value of $A + R_1^b - c_L$ with a probability of $1 - q$. Other firms would emerge from prepack with a probability of $q$. For emerging firms, a good state occurs at a probability of $p$, and the value realized is $A + R_1^g - c_P + R_2^g$. In contrast, if a bad state is realized at a probability of $1 - p$, the firm would be liquidated and receive a value of $A + R_1^g - c_P + R_2^b - c_L$. Overall, the expected value for firms under pre-packaged bankruptcy is

$$V_p = (A + R_1^b - c_L)(1 - q) + q[(A + R_1^g - c_P + R_2^g)p + (A + R_1^g - c_P + R_2^b - c_L)(1 - p)].$$

(1)

The emergence constraint ensures that firms do not prefer earlier liquidation. That is, the expected value of reorganization needs to exceed the liquidation value.

$$[A + R_1^g - c_P + R_2^g]p + [A + R_1^g - c_P + R_2^b - c_L](1 - p) > A + R_1^g - c_L$$

Restructuring the function, we obtain

$$(c_L - c_P) + (pR_2^g + (1 - p)R_2^b) > (1 - p)c_L$$

The left side of the function indicates the benefit of going through pre-packaged reorganization. The first term represents the cost-saving benefit from choosing reorganization instead of liquidation, and the second term represents the expected future cash flow that would be foregone if liquidation occurs at time 1. The right side of function indicates the cost of pre-packaged reorganization. When inefficient firms emerge from bankruptcy, extra liquidation costs occur at a probability of $1 - p$.

Traditional Chapter 11
For traditional Chapter 11, there are two types of firms that fail to emerge: those that have a bad cash flow state at time 1 and those that have a good state but that receive a bad signal. The former are liquidated at a value of $A + R_1^b - c_L$ with a probability of $1 - q$, and the latter are liquidated at a value of $A + R_1^g - c_L$ with a probability of $q(1 - p)$. Overall, a greater portion of the firms $1 - qp > 1 - q$ do not emerge from traditional Chapter 11. For the emerging firm, $1 - \varepsilon$ of them would be in a good state with a value of $A + R_1^g - c_T + R_2^g$ and a portion of $\varepsilon$ would be in a bad state with a liquidation value of $A + R_1^g - c_T + R_2^b - c_L$. Overall, the expected value for firms under traditional Chapter 11 is

$$V_T = (A + R_1^b - c_L)(1 - q) + (A + R_1^g - c_L)q(1 - p) + qp[(1 - \varepsilon)(A + R_1^g - c_T + R_2^g) + \varepsilon(A + R_1^g - c_T + R_2^b - c_L)]$$

(2)

There are two emergence constraints for the traditional bankruptcy scheme. First, the expected value of reorganization after receiving a good signal should exceed the liquidation value. That is, $A + R_1^g - c_L < (A + R_1^g - c_T + R_2^g)(1 - \varepsilon) + (A + R_1^g - c_T + R_2^b - c_L)\varepsilon$. Second, the expected value of reorganization after receiving a bad signal should be less than the liquidation value. That is, $(1 - p)(A + R_1^g - c_L) > (A + R_1^g - c_T + R_2^g)p\varepsilon + (A + R_1^g - c_T + R_2^b - c_L)(1 - p - p\varepsilon)$.

Reorganizing the two constraints, we obtain

$$(c_L - c_T) + \left((1 - \varepsilon)R_2^g + \varepsilon R_2^b\right) - \varepsilon c_L > 0$$

$$c_L - c_T + (\frac{p\varepsilon}{1 - p}R_2^g + \frac{1 - p - p\varepsilon}{1 - p}R_2^b) - \frac{1 - p - p\varepsilon}{1 - p}c_L < 0$$

The first condition states that the benefits of reorganization exceed its cost if a good signal is observed, whereas the second condition states that the benefits of reorganization do not exceed its cost if a bad signal is observed. Combining these two conditions, we obtain $1 > p + \varepsilon$. Given this, we can determine the post-bankruptcy probability that $R_2$ is in a good state through
traditional Chapter 11 \((1 - \varepsilon)\) is higher than the post-bankruptcy probability that \(R_2\) is in a good state through pre-packaged Chapter 11 \((p)\). Thus, firms undergoing traditional Chapter 11 are less likely to refile since some inefficient firms are recognized and filtered from efficient firms.
A2.1 Conflicts and wealth transfer

Denote the senior claim as $S$ and the expected firm value as $V$. We can obtain the senior creditors’ payoff $V_S = \min(S, V)$. The payoff for junior creditors will be $V_j = V - \min(S, V) = \max(0, V - S)$. Next, we define the surplus $S^j$ (or deficit if negative) by choosing traditional Chapter 11 over prepack for the junior creditors and senior creditors separately: $S^j = V_t^j - V_p^j$ and $j \in \{\text{firm, junior, senior}\}$. Given $V = V_j + V_S$, we can get $S^{firm} = S^{\text{junior}} + S^{\text{senior}}$.

One representative creditor would choose traditional Chapter 11 when $S^{\text{firm}} > 0$ and choose prepack otherwise. For two creditors, when $S^{\text{firm}} > 0$ and $S^{\text{junior}} * S^{\text{senior}} < 0$, conflicts arise. Without losing generally, we assume $S^{\text{senior}} > 0$ and $S^{\text{junior}} < 0$. Since $S^{\text{firm}} = S^{\text{junior}} + S^{\text{senior}} > 0$, we obtain $|S^{\text{senior}}| > |S^{\text{junior}}|$. Then, senior creditors can always compensate junior creditors by an amount $|S^{\text{junior}}|$ such that junior creditors become indifferent between prepack and traditional Chapter 11. For senior creditors, their payoff will be $S^{\text{senior}} - |S^{\text{junior}}| = S^{\text{junior}} + S^{\text{senior}} = S^{\text{firm}} > 0$. This compensation mechanism can make the two-creditors setting identical to the representative-creditor setting. The same argument can apply when $S^{\text{firm}} < 0$.

A2.2 Debt-Equity conflicts

Debt-Equity conflicts occur when equity holders are not behaving in the best interest of the firm and debt holders. Equity holders are junior claimholders, having limited liability and making final bankruptcy decisions. To be consistent with previous notations, we denote that Equity = Junior, Debt = Senior. We can generalize Debt-Equity conflicts as $|S^{\text{senior}}| > |S^{\text{junior}}|$, $S^{\text{junior}} * S^{\text{senior}} < 0$. When $S^{\text{junior}} < 0$, equity holders prefer prepack when debt holders prefer traditional Chapter 11 and Chapter 11 is the firm’s optimal choice. When
\( S_{junior} > 0 \), vice versa. We will illustrate using the example of \( S_{junior} < 0 \) for the rest of this part. The proof for \( S_{junior} > 0 \) is symmetric.

Scenario 1: Mutual agreement.

Without equity holder’s decision rights, senior claimholders (i.e., creditors) can transfer a portion of their surplus (i.e., \( |S_{junior}| \)) to equity holders and make them indifferent between prepack and traditional Chapter 11. Equity is Junior claim in 2.1.

Scenario 2: No cramdown

With absolute bargaining power, equity holders will extract all surplus (i.e., \( |S^{firm}| \)) and make creditors indifferent between prepack and traditional Chapter 11.

Scenario 3: Cramdown based on bankruptcy procedures.

Equity holders face constraints as the court may strip their decision power. This can occur when the court finds equity holders are not acting in the best interests of the firm (i.e., maximizing the firm’s expected value). If equity holders choose the suboptimal choice (prepack), cramdown can occur at a fixed probability of \( \mu \). Then, the court will act in the interests of the creditors and choose traditional Chapter 11. In cramdown, creditors will get full surplus \( |S^{senior}| \) without any need for wealth transfer and equity holders receive \( S_{junior} < 0 \).

If equity holders choose prepack and cramdown does not occur, they avoid losing \( S_{junior} \). Overall, no wealth transfer occurs in the suboptimal choice. Additionally, equity holders demand a proportion of \( x \) to choose the optimal bankruptcy procedure (i.e., Traditional Chapter 11 in this case).

Equity holders would choose traditional Chapter 11 when

\[
x \cdot S^{senior} + S_{junior} \geq \mu \cdot S_{junior} + (1 - \mu) \cdot 0 \tag{1}
\]

Creditors would choose traditional Chapter 11 when
\[(1 - x) \cdot S^{senior} \geq \mu \cdot S^{senior} + (1 - \mu) \cdot 0 \quad [2]\]

Both parties agree on choosing traditional Chapter 11 if and only if

\[1 - \mu \geq x \geq (1 - \mu) \cdot \frac{|S^{junior}|}{S^{senior}} \quad [3]\]

The wealth transfer in equation [3] is always obtainable since \(|S^{senior}| > |S^{junior}|.| \)

Scenario 4: Cramdown based on deviation from APR.

Equity holders demand a proportion of \(x\). The probability \(f(x)\) of cramdown is a function of \(x\). We assume \(f(x)\) is an increase function of \(x\). In prepack, there will be no wealth transfer.

To make traditional chapter 11 more attractive, the expected payoff for equity holders in traditional Chapter 11 \((1 - f(x)) \cdot x \cdot S^{senior}\) needs to be higher than \(|S^{junior}|.| \)

Equity holders would choose traditional Chapter 11 when

\[ (1 - f(x)) \cdot (x \cdot S^{senior} + S^{junior}) + f(x) \cdot S^{junior} > 0 \quad [4]\]

Creditors would choose traditional Chapter 11 when

\[ (1 - f(x)) \cdot (1 - x) \cdot S^{senior} + f(x) \cdot S^{senior} > 0 \quad [5]\]

Equation [5] is always satisfied when \(x > 0\). From equation [4], we can obtain

\[ (1 - f(x)) \cdot x \cdot S^{senior} + S^{junior} > 0 \quad [6]\]

Equation [6] cannot always be satisfied. To illustrate that, we assume \(f(x) = x\). Then, equation [6] is only satisfied when \(|S^{senior}| > 4|S^{junior}|.| \)


1.10 Tables and Figures

Figure 1: Rise of Pre-packaged Chapter 11

The picture presents the percentage ratio of Pre-packaged Chapter 11 in Chapter 11 cases from 1980 to 2014. There are 959 Chapter 11 cases included in the sample; 679 cases are through traditional Chapter 11, and 280 cases are through pre-packaged or pre-negotiated Chapter 11. In each year, we calculate the prepack % = (number of prepack cases filed) / (number of prepack cases filed + number of traditional Chapter 11 cases filed).
Figure 2
Traditional Chapter 11 vs Prepack Chapter 11 Firms’ Pre-bankruptcy and Post-bankruptcy Performances

Figure 2.1 compares the industry adjusted mean of firms’ pre-bankruptcy performance between the traditional Chapter 11 group and the prepack Chapter 11 group. It presents averages of Altman’s (1968, 2000) Z-score for firms’ financial distress level. The Z-score is calculated as follows:

$$z = 1.2 \times \frac{\text{returns earned}}{\text{total assets}} + 3.3 \times \frac{\text{earnings before interest and tax}}{\text{total assets}} + 0.6 \times \frac{\text{market value of equity}}{\text{book value of total liabilities}} + \frac{\text{working capital}}{\text{sales}} + 1.4.$$  

Figures 2.2 to 2.4 compares the average of firms’ post-bankruptcy outcomes between the traditional Chapter 11 group and the prepack Chapter 11 group. Figure 2.2 presents their average refile rates within 5 years after firm emergence from bankruptcy. Figure 2.3 presents averages of emergence rate for firms. Figure 2.4 presents averages of refiling rate after the firm emerges from bankruptcy.

2.1: Altman’s Z-score

2.2: Refiling rate in 5 years

2.3: Emergence rate

2.4: Refile rate
Figure 3
Legal Process of Traditional Chapter 11

1. Petition
   - **Debtor:**
     - Filing bankruptcy
     - Clarify biggest 25 Creditors
   - **Creditors:**
     - Filing bankruptcy
   - **Court:**
     - Approve/Decline motions

2. Plan Formation
   - Automatic stay (120 days up to 18 months if extended after petition date)
   - File motions
   - File proofs of claims
   - File motions

3. Plan Confirmation
   - File disclosure statement
   - File plan of reorganization
   - Up to 20 months after petition date
   - File plan of reorganization
   - **Vote plan**
   - Approve disclosure statement
   - Confirm plan of reorganization after votes

4. Plan implementation period
   - Implement/Modify the Plan
   - Oversee the implementation
   - Confirm modifications
   - Close the case
Table 1
Statistical Summary

This table presents the statistical summary of the variables. We separate the whole sample into two subsamples: Traditional Chapter 11 Sample and Pre-packaged Chapter 11 Sample. **Panel A** presents the firm’s financial variables both at filing and at emerging: Size is the log amount of the firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. In addition, we present two variables of interest based on the data at filing: specific asset represents the value of plants, property and equipment as a percentage of total assets; Intangible ratio is intangible assets as a percentage of total assets. All variables are winsorized at 1% in Panel A. **Panel B** presents the pre-bankruptcy characteristics of bankrupted firms. Employee efficiency is the last reported sale before the firm’s bankruptcy divided by the number of employees when the firm files bankruptcy. Asset volatility is calculated based on the Merton (1974) model. The Z-score is the financial distress index introduced in Altman (1968, 2000). The Z-score is calculated as follows: \[ Z = 1.2 \times \frac{\text{working capital}}{\text{total assets}} + 1.4 \times \frac{\text{book value of total liabilities}}{\text{total assets}} + 3.3 \times \frac{\text{earnings before interest and tax}}{\text{total assets}} + 0.6 \times \frac{\text{market value of equity}}{\text{book value of total liabilities}} + \text{sales} \]. ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets. **Panel C** presents the bankruptcy outcomes, including emerge as an indicator that equals 1 if a firm emerges from reorganization through Chapter 11 and 0 if a firm fails to emerge through Chapter 11; refile within 5 years as an indicator variable whether a firm files a bankruptcy within 5 years after it emerges from previous bankruptcy; days in Bankruptcy as a measure of the number of days from the date of bankruptcy filing to the date of the court’s confirmation of the bankruptcy plan; News coverage is the number of firm-specific bankruptcy news items that appear in the RavenPack Dow Jones Equities data around the firm’s bankruptcy period. Specifically, our sample period for a firm’s bankruptcy news is from 6 months before its bankruptcy filing to 1 year after the firm emerges; log(No. of docket files) is the log of the number of files in docket when the court confirms the firm’s plan of reorganization; Direct fee is the amount of the professional fee paid during the reorganization procedure as a percentage of total assets before bankruptcy; CEO turnover as an indicator that equals 1 if a firm changes its CEO during its bankruptcy process and 0 otherwise; and DIP financing as an indicator variable that equals 1 when the firm obtains debtor-in-possession financing during bankruptcy and 0 otherwise.

**Panel A: Financial Variables**

<table>
<thead>
<tr>
<th>Financial Variables</th>
<th>Traditional Chapter 11 Sample</th>
<th>Pre-packaged Chapter 11 Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.  Mean  Std. Dev.  Min  Max</td>
<td>Obs.  Mean  Std. Dev.  Min  Max</td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>621  0.9495  0.3761  0.2810  2.7757</td>
<td>254  1.1380  0.4189  0.2901  2.7757</td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>513  1.3333  1.1522  0.0608  6.9796</td>
<td>225  0.9802  0.8842  0.2901  6.9796</td>
</tr>
<tr>
<td>ROA at filing</td>
<td>613  -0.0363  0.1322  -0.6660  0.1579</td>
<td>253  -0.0190  0.1292  -0.6660  0.1579</td>
</tr>
<tr>
<td>Investment 2 years before filing</td>
<td>587  0.0674  0.0914  0.0000  0.4732</td>
<td>245  0.0543  0.0717  0.0000  0.4417</td>
</tr>
<tr>
<td>Size at Emerging</td>
<td>222  1.1394  1.6389  -3.1113  5.2264</td>
<td>144  1.2879  1.1855  -2.2826  5.2264</td>
</tr>
<tr>
<td>Leverage at Emerging</td>
<td>193  0.8380  0.4579  0.1758  2.9308</td>
<td>130  0.8727  0.3458  0.1758  2.3878</td>
</tr>
<tr>
<td>Current ratio at Emerging</td>
<td>167  1.8660  1.0721  0.1426  6.5982</td>
<td>116  1.5422  0.9254  0.1428  5.0426</td>
</tr>
<tr>
<td>ROA at Emerging</td>
<td>194  0.0163  0.1065  -0.7100  0.2266</td>
<td>128  -0.0168  0.1512  -0.7100  0.2266</td>
</tr>
<tr>
<td>Investment 1 year after Emergence</td>
<td>186  0.0433  0.0449  0.0000  0.2497</td>
<td>127  0.0363  0.0401  0.0000  0.2497</td>
</tr>
<tr>
<td>Specific Assets</td>
<td>269  0.4078  0.2380  0.0000  0.9371</td>
<td>143  0.3640  0.2717  0.0000  0.9411</td>
</tr>
<tr>
<td>Intangible ratio</td>
<td>246  0.0663  0.1216  0.0000  0.7097</td>
<td>138  0.1805  0.2126  0.0000  0.7097</td>
</tr>
</tbody>
</table>
### Panel B: Pre-bankruptcy characteristics

<table>
<thead>
<tr>
<th>Pre-bankruptcy</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment efficiency</td>
<td>674</td>
<td>0.4217</td>
<td>1.6598</td>
<td>0.0003</td>
<td>31.9250</td>
<td>277</td>
<td>0.6743</td>
<td>3.8803</td>
<td>0.0114</td>
<td>60.1090</td>
</tr>
<tr>
<td>Asset volatility</td>
<td>140</td>
<td>0.1068</td>
<td>0.0915</td>
<td>0.0018</td>
<td>0.3595</td>
<td>85</td>
<td>0.0958</td>
<td>0.1066</td>
<td>0.0019</td>
<td>0.3595</td>
</tr>
<tr>
<td>Altman's Z-Score</td>
<td>204</td>
<td>-0.4254</td>
<td>6.3040</td>
<td>-80.4021</td>
<td>8.2431</td>
<td>105</td>
<td>0.1501</td>
<td>2.4165</td>
<td>-15.2057</td>
<td>3.7526</td>
</tr>
<tr>
<td>ROA at filing</td>
<td>613</td>
<td>-0.0363</td>
<td>0.1322</td>
<td>-0.6660</td>
<td>0.1759</td>
<td>253</td>
<td>-0.0190</td>
<td>0.1292</td>
<td>-0.6660</td>
<td>0.1759</td>
</tr>
</tbody>
</table>

### Panel C: Bankruptcy outcomes

<table>
<thead>
<tr>
<th>Bankruptcy outcomes</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emerge</td>
<td>679</td>
<td>0.6112</td>
<td>0.4878</td>
<td>0</td>
<td>1</td>
<td>280</td>
<td>0.8750</td>
<td>0.3313</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Refile in 5 years</td>
<td>338</td>
<td>0.1479</td>
<td>0.3556</td>
<td>0</td>
<td>1</td>
<td>166</td>
<td>0.2349</td>
<td>0.4252</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Days in bankruptcy</td>
<td>679</td>
<td>678</td>
<td>531</td>
<td>13</td>
<td>4468</td>
<td>280</td>
<td>184</td>
<td>257</td>
<td>18</td>
<td>2015</td>
</tr>
<tr>
<td>News coverage</td>
<td>57</td>
<td>8.9649</td>
<td>7.6320</td>
<td>1</td>
<td>32</td>
<td>50</td>
<td>6.96</td>
<td>6.3212</td>
<td>1</td>
<td>28</td>
</tr>
<tr>
<td>log(No. of docket files)</td>
<td>475</td>
<td>7.3967</td>
<td>0.9590</td>
<td>4.4067</td>
<td>10.0443</td>
<td>244</td>
<td>5.8941</td>
<td>0.9709</td>
<td>2.9957</td>
<td>9.1528</td>
</tr>
<tr>
<td>Direct fee</td>
<td>72</td>
<td>0.0351</td>
<td>0.0251</td>
<td>0.0020</td>
<td>0.1161</td>
<td>79</td>
<td>0.0204</td>
<td>0.0169</td>
<td>0.0012</td>
<td>0.1050</td>
</tr>
<tr>
<td>CEO turnover</td>
<td>633</td>
<td>0.5687</td>
<td>0.4956</td>
<td>0</td>
<td>1</td>
<td>254</td>
<td>0.1417</td>
<td>0.3495</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>DIP financing</td>
<td>523</td>
<td>0.6788</td>
<td>0.4674</td>
<td>0</td>
<td>1</td>
<td>242</td>
<td>0.6405</td>
<td>0.4808</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
Figure 4
Refiling Rate 5 Years after Emergence for Traditional vs Prepack Chapter 11

This bar chart presents the refile rate within the 5 years after firms emerge from bankruptcy. Years from emergence to refiling are based on the firm’s emergence date to the refile date. From year 1 to year 5, the refile rate for prepack in year $i$ is calculated as the number of prepack firms that refile in year $i$ divided by the total number of firms that emerge from prepack in our sample, where $i \in \{1,2,3,4,5\}$. From year 1 to year 5, the refile rate for traditional Chapter 11 in year $i$ is calculated as the number of traditional Chapter 11 firms that refile in year $i$ divide by the total number of firms that emerge from traditional Chapter 11 in our sample, where $i \in \{1,2,3,4,5\}$.
Figure 5

Post-bankruptcy Performance for Traditional and Pre-packaged Chapter 11

The figures present the firms’ annual EBIT Margin from year 1 to year 5 after they emerge from traditional Chapter 11 bankruptcy and prepack. EBIT Margin equals annual earnings before interest and tax (EBIT) as a percentage ratio of annual sales, which represents firms’ post-bankruptcy profitability performance. From the highest to the lowest, the figures show 5th percentile, 10th percentile, 25th percentile, 50th percentile, 75th percentile, 90th percentile and 95th percentile of firms’ EBIT margin for a particular year. The number of observations decreases by year, as sample size drops with the firms’ exit.

Panel A
Post-bankruptcy Performance for Traditional Chapter 11

Panel B
Post-bankruptcy Performance for Pre-packaged or Pre-negotiated Chapter 11
Figure 6
Bankruptcy Decision-Making Process

Creditor's Choice

Decision Period
- Prepack
  - 1-q
  - q

- Traditional Chapter 11
  - 1-q
  - q

liquidity Period
- Liquidation
  - Emerge
    - \( A + R_1^b - c_L \)

Signal Period
- Liquidation
  - \( A + R_1^b - c_L \)
  - \( 1-p \)
    - \( p \)

- Stay in bankruptcy
  - \( A + R_1^b - c_L \)
  - \( 1-p \)
    - \( p \)

Solvency Period
- Liquidation
  - \( A + R_1^g - c_L \)
  - \( 1-p \)
    - \( p \)

- Continue
  - \( A + R_1^g - c_p + R_2^g \)

- Liquidation
  - \( A + R_1^g - c_T + R_2^g \)
  - \( 1-p \)
    - \( p \)

- Continue
  - \( A + R_1^g - c_T + R_2^g \)
### Table 2

**Model Bankruptcy Outcomes for Pre-packaged Chapter 11 vs Traditional Chapter 11**

This table presents the theoretical probability of outcomes from our model. Scenario (1): Probability $q$ is the probability of a good state in time 1 for Cash flow $R_1$. Prepack firms emerge as long as $R_1$ is in a good state. Therefore, a $1 - q$ proportion of prepack firms will realize a bad state and cannot emerge. For traditional Chapter 11, in addition to the $1 - q$ proportion of firms, firms in a good state for $R_1$ but receive a bad signal would not emerge with a probability of $q(1 - p)$. Thus, the non-emergence rate would be $1 - q + q(1 - p)$ for traditional Chapter 11. Scenario (2) & (3): The refile rate for prepack would be $q(1 - p)$ since $q$ proportion emerged and $(1 - p)$ of them would be in a bad state at time 3 for $R_2$. $(1 - p)$ is the conditional refile rate condition on prepack firms’ emergence. The total refile rate for traditional Chapter 11 would be $qp\epsilon$ since $qp$ proportion emerged and $\epsilon$ of them would be in a bad state at time 3 for $R_2$. $\epsilon$ is the conditional refile rate conditional on traditional Chapter 11 firms’ emergence. Appendix 1 shows $1 > \epsilon + p$. From that, it is easy to show both (2) and (3) hold.

<table>
<thead>
<tr>
<th></th>
<th>Pre-packaged Chapter 11</th>
<th>$\geq$, $\leq$, $&lt;$</th>
<th>Traditional Chapter 11</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1): Not Emerge</td>
<td>$1 - q$</td>
<td>$&lt;$</td>
<td>$1 - q + q(1 - p)$</td>
</tr>
<tr>
<td>(2): Refile Ratio (prior)</td>
<td>$q(1 - p)$</td>
<td>$&gt;$</td>
<td>$qp\epsilon$</td>
</tr>
<tr>
<td>(3): Refile Ratio (conditional)</td>
<td>$(1 - p)$</td>
<td>$&gt;$</td>
<td>$\epsilon$</td>
</tr>
</tbody>
</table>
Table 3: Refile and Prepack

The table presents the logistic regression results for firm refile. The dependent variable is Refile in 5 years, which is an indicator variable that equals 1 if a firm files a bankruptcy again within 5 years after it emerges from previous bankruptcy and 0 otherwise. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if it emerges from a traditional Chapter 11. We control for a range of firm financial variables at filing and/or at emergence: Size is the log amount of the firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. Additional variables of interest are as follows: Intangible ratio is the intangible assets as a percentage of total assets; DIP financing is an indicator variable that equals 1 when the firm obtains debtor-in-possession financing during bankruptcy and 0 otherwise. Model (1) regresses refiling within 5 years on prepack while controlling for financial variables at filing and Intangible ratio. Model (2) regresses refiling within 5 years on prepack while controlling for financial variables at emergence and Intangible ratio. Model (3) represents our main result. It regresses refiling within 5 years on prepack while controlling for financial variables both at filing and at emergence plus Intangible ratio. Model (4) regresses refiling within 5 years on financial variables both at filing and at emergence plus Intangible ratio without prepack. Model (5) controls for DIP financing. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepack</td>
<td>0.760**</td>
<td>0.895***</td>
<td>1.193***</td>
<td>2.147***</td>
<td>1.666***</td>
</tr>
<tr>
<td></td>
<td>(2.33)</td>
<td>(2.81)</td>
<td>(2.58)</td>
<td>(6.63)</td>
<td>(3.67)</td>
</tr>
<tr>
<td>Intangible ratio</td>
<td>0.770</td>
<td>0.755</td>
<td>0.993</td>
<td>1.837</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.71)</td>
<td>(0.88)</td>
<td>(0.92)</td>
<td>(1.40)</td>
<td></td>
</tr>
<tr>
<td>Intangible assets/Total assets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DIP financing</td>
<td></td>
<td></td>
<td></td>
<td>1.666***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(3.67)</td>
<td></td>
</tr>
<tr>
<td>Size at filing</td>
<td>-0.328**</td>
<td>-0.216</td>
<td>-0.276</td>
<td>-0.305</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.34)</td>
<td>(-0.99)</td>
<td>(-1.21)</td>
<td>(-0.72)</td>
<td></td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>-0.406</td>
<td>-0.430</td>
<td>-0.280</td>
<td>0.208</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.38)</td>
<td>(-1.01)</td>
<td>(-0.92)</td>
<td>(0.61)</td>
<td></td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>0.060</td>
<td>0.184</td>
<td>0.117</td>
<td>0.550**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.33)</td>
<td>(0.91)</td>
<td>(0.61)</td>
<td>(2.50)</td>
<td></td>
</tr>
<tr>
<td>ROA at filing</td>
<td>-1.822</td>
<td>-0.243</td>
<td>-0.720</td>
<td>2.027</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.12)</td>
<td>(-0.15)</td>
<td>(-0.46)</td>
<td>(0.44)</td>
<td></td>
</tr>
<tr>
<td>Investment 2 years before filing</td>
<td>-1.828</td>
<td>-1.559</td>
<td>-0.504</td>
<td>-5.246***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.72)</td>
<td>(-0.34)</td>
<td>(-0.12)</td>
<td>(-3.41)</td>
<td></td>
</tr>
<tr>
<td>Size at Emergence</td>
<td>-0.308</td>
<td>-0.166</td>
<td>-0.091</td>
<td>0.119</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.08)</td>
<td>(-0.34)</td>
<td>(-0.22)</td>
<td>(0.22)</td>
<td></td>
</tr>
<tr>
<td>Leverage at Emergence</td>
<td>0.651</td>
<td>0.556</td>
<td>0.517</td>
<td>0.060</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
<td>(1.01)</td>
<td>(0.90)</td>
<td>(0.09)</td>
<td></td>
</tr>
<tr>
<td>Current ratio at Emergence</td>
<td>-0.117</td>
<td>-0.459***</td>
<td>-0.468**</td>
<td>-1.142***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.75)</td>
<td>(-3.06)</td>
<td>(-2.42)</td>
<td>(-3.34)</td>
<td></td>
</tr>
<tr>
<td>ROA at Emergence</td>
<td>-1.788</td>
<td>-0.966</td>
<td>-2.061</td>
<td>-1.252</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.56)</td>
<td>(-0.55)</td>
<td>(-1.24)</td>
<td>(-0.30)</td>
<td></td>
</tr>
<tr>
<td>Investment 1yr after Emergence</td>
<td>3.736*</td>
<td>6.612***</td>
<td>3.254</td>
<td>14.633</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.68)</td>
<td>(2.86)</td>
<td>(1.07)</td>
<td>(1.60)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.852</td>
<td>-2.271***</td>
<td>-1.325</td>
<td>-0.865</td>
<td>-2.638**</td>
</tr>
<tr>
<td></td>
<td>(-1.30)</td>
<td>(-2.63)</td>
<td>(-1.18)</td>
<td>(-0.84)</td>
<td>(-1.78)</td>
</tr>
<tr>
<td>Observations</td>
<td>181</td>
<td>196</td>
<td>148</td>
<td>148</td>
<td>101</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.0705</td>
<td>0.0936</td>
<td>0.142</td>
<td>0.106</td>
<td>0.236</td>
</tr>
</tbody>
</table>
Table 4
Prepack and Refiling Rate: 2SLS Results

The table presents the two-stage least square regression results for firms’ refiling ratios. The dependent variable is firms’ refiling within 5 years. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from a traditional Chapter 11. We control for a range of firm financial variables at filing: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. The first-stage regression includes an instrument to capture the non-risk determinants of prepack: Docket number is the log of the number of files in docket when the court confirms the firm’s plan of reorganization. Robust t-statistics are shown in parentheses (with standard errors clustered by firm). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First Stage</td>
<td>Second Stage</td>
</tr>
<tr>
<td>Docket number</td>
<td>-0.291***</td>
<td>0.167*</td>
</tr>
<tr>
<td>log(number of files in docket)</td>
<td>(-18.04)</td>
<td>(1.76)</td>
</tr>
<tr>
<td>Prepack</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size at filing</td>
<td>0.060***</td>
<td>-0.032</td>
</tr>
<tr>
<td>(3.26)</td>
<td>(-1.31)</td>
<td></td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>-0.036</td>
<td>-0.002</td>
</tr>
<tr>
<td>(-0.57)</td>
<td>(-0.03)</td>
<td></td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>-0.002</td>
<td>-0.004</td>
</tr>
<tr>
<td>(-0.12)</td>
<td>(-0.20)</td>
<td></td>
</tr>
<tr>
<td>ROA at filing</td>
<td>-0.482*</td>
<td>0.076</td>
</tr>
<tr>
<td>(-1.94)</td>
<td>(0.27)</td>
<td></td>
</tr>
<tr>
<td>Investment 2 years before filing</td>
<td>-0.643</td>
<td>-0.156</td>
</tr>
<tr>
<td>(-1.08)</td>
<td>(-0.34)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.413***</td>
<td>0.202*</td>
</tr>
<tr>
<td>(16.6)</td>
<td>(1.72)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>127</td>
<td>127</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.292</td>
<td>0.110</td>
</tr>
</tbody>
</table>
Table 5
Single-failure Cox-Hazard Model

This table presents the single-failure Cox-Hazard regression results. The dependent variable is the failure dummy: refile indicator variable for firms emerging from reorganization. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from a traditional Chapter 11. Pre-packed reorganization is a case where all claimholders of the firm pre-agree on the plan of reorganization before the firm files Chapter 11. Pre-negotiation reorganization is a case where at least one of the claimholders of the firm pre-agrees on the plan of reorganization before the firm files Chapter 11. We control for a range of financial variables: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. Year fixed effects are controlled for in model (1). Alternatively, GDP as the real GDP index of a given year is included in model (2). Industry fixed effects based on firms’ SIC Division are controlled for in both models (1) and (2). Robust t-statistics are shown in parentheses (with standard errors clustered by firm). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepack</td>
<td>1.304*** (4.07)</td>
<td>1.351*** (4.42)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.035 (-0.35)</td>
<td>-0.023 (-0.23)</td>
</tr>
<tr>
<td>Current Ratio</td>
<td>-0.224 (-1.53)</td>
<td>-0.226 (-1.54)</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.029 (0.08)</td>
<td>0.029 (0.09)</td>
</tr>
<tr>
<td>ROA</td>
<td>-2.990* (-1.84)</td>
<td>-2.813* (-1.89)</td>
</tr>
<tr>
<td>Investment</td>
<td>-8.290* (-1.80)</td>
<td>-7.730* (-1.81)</td>
</tr>
<tr>
<td>GDP</td>
<td>-0.054*** (-5.33)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,717</td>
<td>1,717</td>
</tr>
<tr>
<td>Industry</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>
Table 6
Emerge and Prepack

The table presents the logistic regression results for firm emergence. The dependent variable is the emergence rate: an indicator that equals 1 if a firm emerges from reorganization through a Chapter 11 and 0 if a firm fails to emerge through a Chapter 11. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from a traditional Chapter 11. We control for a range of a firm’s financial variables at filing: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. Additional variables of interest include the intangible ratio, which is intangible assets as a percentage of total assets, and DIP financing, which is an indicator variable that equals 1 when the firm obtains debtor-in-possession financing during bankruptcy and 0 otherwise. Model (1) regresses the emergence rate on prepack while controlling for financial variables at filing and the Intangible ratio. Model (2) regresses the emergence rate while controlling only for financial variables at filing and Intangible ratio. Model (3) adds an interaction term of prepack with intangible ratio to model (1). Model (4) controls for DIP financing. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Controls at filing</th>
<th>(2) Without prepack</th>
<th>(3) Intangible interaction</th>
<th>(4) DIP financing</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prepack</strong></td>
<td>1.430**</td>
<td>2.015**</td>
<td>1.618***</td>
<td>0.846***</td>
</tr>
<tr>
<td></td>
<td>(2.01)</td>
<td>(2.56)</td>
<td>(4.27)</td>
<td>(3.12)</td>
</tr>
<tr>
<td>Prepack X intangible ratio</td>
<td>-1.125</td>
<td>0.324</td>
<td>0.622</td>
<td>-3.741</td>
</tr>
<tr>
<td></td>
<td>(-0.52)</td>
<td>(0.18)</td>
<td>(0.12)</td>
<td></td>
</tr>
<tr>
<td>Intangible ratio:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total assets/Total assets</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DIP financing</td>
<td></td>
<td></td>
<td></td>
<td>0.846***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(3.12)</td>
</tr>
<tr>
<td>Size at filing</td>
<td>0.149*</td>
<td>0.093</td>
<td>0.143*</td>
<td>0.171***</td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td>(1.02)</td>
<td>(1.78)</td>
<td>(2.69)</td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>1.109</td>
<td>1.209</td>
<td>1.111</td>
<td>1.103***</td>
</tr>
<tr>
<td></td>
<td>(1.02)</td>
<td>(1.07)</td>
<td>(1.07)</td>
<td>(3.81)</td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>-0.233***</td>
<td>-0.267***</td>
<td>-0.222***</td>
<td>-0.235***</td>
</tr>
<tr>
<td></td>
<td>(-4.28)</td>
<td>(-4.85)</td>
<td>(-3.43)</td>
<td>(-3.23)</td>
</tr>
<tr>
<td>ROA at filing</td>
<td>2.349</td>
<td>1.216</td>
<td>2.173</td>
<td>1.522**</td>
</tr>
<tr>
<td></td>
<td>(1.61)</td>
<td>(0.59)</td>
<td>(1.36)</td>
<td>(2.39)</td>
</tr>
<tr>
<td>Investment 2 years before filing</td>
<td>-2.607</td>
<td>-1.783</td>
<td>-2.614</td>
<td>-1.825***</td>
</tr>
<tr>
<td></td>
<td>(-0.90)</td>
<td>(-0.69)</td>
<td>(-0.91)</td>
<td>(-4.16)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.962</td>
<td>1.102</td>
<td>0.848</td>
<td>-0.986***</td>
</tr>
<tr>
<td></td>
<td>(0.91)</td>
<td>(0.98)</td>
<td>(0.81)</td>
<td>(-2.71)</td>
</tr>
<tr>
<td>Observations</td>
<td>256</td>
<td>256</td>
<td>256</td>
<td>402</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.0787</td>
<td>0.0437</td>
<td>0.0871</td>
<td>0.153</td>
</tr>
</tbody>
</table>
Table 7
Determinants of Prepack

The table presents the logistic regression results for prepack. The dependent variable is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from traditional Chapter 11. The independent variables of interest include the intangible ratio, which is intangible assets as a percentage of total assets; specific assets, which is the value of plants, property and equipment as percentage of total assets; and the Z-score, which is the financial distress index introduced in Altman (1968, 2000).

The Z-score is calculated as follows: $Z = 1.2 \times \frac{\text{working capital \_ sales}}{\text{total assets}} + 1.4 \times \frac{\text{retained earning \_ sales}}{\text{total assets}} + 0.6 \times \frac{\text{Earnings before interest and tax}}{\text{total assets}} + \text{log} \left( \frac{\text{market value of equity \_ unsecured claims}}{\text{book value of total liabilities \_ unsecured claims}} \right)$. The bargaining power is calculated as $\log \left( \frac{\text{secured claims}}{\text{total liabilities}} \right)$. We control for a range of firm financial variables at filing: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. Model (1) regresses prepack on intangible ratio and control variables. Model (2) drops intangible ratio in the regression. Model (3) adds both intangible ratio and specific ratio. Model (4) regresses prepack on Z-score. Models (1)-(4) control for industry fixed effects based on firms’ SIC Division and year fixed effects based on firms’ year of filing bankruptcy. Model (5) only controls industry-fixed effects based on firms’ SIC Division. Model (6) only controls year-fixed effects based on firms’ year of filing bankruptcy. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Prepack</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td><strong>Intangible ratio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intangible assets/Total assets</td>
<td>5.557***</td>
<td>6.906***</td>
<td>6.083***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specific Assets:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPE/Total assets</td>
<td></td>
<td>1.057</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Z-score</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.089***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(3.69)</td>
<td></td>
</tr>
<tr>
<td><strong>Bargaining power</strong></td>
<td></td>
<td>0.007</td>
<td>0.091</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.06)</td>
<td>(0.76)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size at filing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.091</td>
</tr>
<tr>
<td>(-3.32)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-1.98)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment 2 years before filing</td>
<td>1.545</td>
<td>1.319</td>
<td>2.773</td>
<td>-0.255</td>
<td>2.866</td>
<td></td>
</tr>
<tr>
<td>ROA at filing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-2.70)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-12.67)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Year Fixed Effect</strong></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Industry Fixed Effect</strong></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td>195</td>
<td>351</td>
<td>161</td>
<td>233</td>
<td>114</td>
</tr>
<tr>
<td></td>
<td></td>
<td>85</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td></td>
<td>0.309</td>
<td>0.148</td>
<td>0.219</td>
<td>0.127</td>
<td>0.279</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.344</td>
</tr>
</tbody>
</table>
### Table 8
#### News during bankruptcy

The table presents the logistic regression results for firm refile. There are two dependent variables: refile and refile in 5 years. Refile is an indicator variable that equals 1 if a firm files a bankruptcy after it emerges from a previous bankruptcy to the end of 2014 and 0 otherwise. Refile in 5 years is an indicator variable that equals 1 if a firm files a bankruptcy again within 5 years after it emerges from a previous bankruptcy and 0 otherwise. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if it emerges from traditional Chapter 11. News is the number of firm-specific bankruptcy news items that appear in the RavenPack Dow Jones Equities data around the firm’s bankruptcy period. Specifically, our sample period for a firm’s bankruptcy news is from 6 months before its bankruptcy filing to 1 year after the firm emerges. Model (1) regresses the refile rate on prepack, news and their interaction term. Model (2) regresses the refile rate within 5 years on prepack, news and their interaction term. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Refile</th>
<th>(2) Refile within 5 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepack</td>
<td>-0.508***</td>
<td>-2.378</td>
</tr>
<tr>
<td></td>
<td>(-3.31)</td>
<td>(-0.98)</td>
</tr>
<tr>
<td>News</td>
<td>-0.013</td>
<td>-0.038</td>
</tr>
<tr>
<td></td>
<td>(-0.35)</td>
<td>(-1.39)</td>
</tr>
<tr>
<td>Prepack X News</td>
<td>0.100***</td>
<td>0.450*</td>
</tr>
<tr>
<td></td>
<td>(5.97)</td>
<td>(1.65)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.028***</td>
<td>-2.700***</td>
</tr>
<tr>
<td></td>
<td>(-6.37)</td>
<td>(-3.88)</td>
</tr>
<tr>
<td>Observations</td>
<td>107</td>
<td>72</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.0351</td>
<td>0.300</td>
</tr>
</tbody>
</table>
Table 9
Prepack and Refiling: CEO Turnover, Professional Fees and Investment

The table presents the logistic regression results for firms’ refile ratios after we control for CEO turnover and professional fees. The dependent variable refiling within 5 years is an indicator variable of whether a firm files bankruptcy within 5 years after it emerges from previous bankruptcy. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from a traditional Chapter 11. We control for a range of firm financial variables both at filing and at emergence: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is total current assets as a percentage of total current liabilities; Leverage is total liabilities as a percentage of total assets; ROA is earnings before Interest and Tax (EBIT) as a percentage of total assets; and Investment is capital expenditure as a percentage of total assets. Ceoturnover is an indicator that equals 1 if a firm changes its CEO during its bankruptcy process and 0 otherwise. Fee1 is the amount of the professional fee paid during the reorganization procedure as a percentage of total assets before bankruptcy. Model (1) regresses refiling within 5 years on prepack while controlling for CEO turnover and its interaction term. Model (2) includes additional financial variables both at filing and at emergence. Model (3) regresses refile in 5 years on prepack controlling for Fee1 and its interaction term with prepack. Model (4) regresses refiling in 5 years on prepack controlling for the interaction terms between different periods of investment and prepack. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th></th>
<th>(1) CEO turnover</th>
<th>(2) CEO turnover</th>
<th>(3) Professional fees</th>
<th>(4) Investment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prepack</strong></td>
<td>0.450***</td>
<td>1.076***</td>
<td>0.455</td>
<td>1.512*</td>
</tr>
<tr>
<td></td>
<td>(2.88)</td>
<td>(3.24)</td>
<td>(0.70)</td>
<td>(1.88)</td>
</tr>
<tr>
<td><strong>Ceoturnover</strong></td>
<td>-0.266</td>
<td>-0.292</td>
<td>-0.056</td>
<td>0.669</td>
</tr>
<tr>
<td></td>
<td>(-0.92)</td>
<td>(-0.68)</td>
<td>(0.93)</td>
<td></td>
</tr>
<tr>
<td><strong>Prepack X Ceoturnover</strong></td>
<td>-0.056</td>
<td>0.669</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Size at filing</strong></td>
<td>-0.216</td>
<td>-0.216</td>
<td></td>
<td>-0.303</td>
</tr>
<tr>
<td></td>
<td>(-0.95)</td>
<td></td>
<td></td>
<td>(-1.52)</td>
</tr>
<tr>
<td><strong>Leverage at filing</strong></td>
<td>-0.191</td>
<td>-0.191</td>
<td></td>
<td>-0.248</td>
</tr>
<tr>
<td></td>
<td>(-0.78)</td>
<td></td>
<td></td>
<td>(-0.73)</td>
</tr>
<tr>
<td><strong>Current ratio at filing</strong></td>
<td>0.113</td>
<td>0.113</td>
<td></td>
<td>0.219</td>
</tr>
<tr>
<td></td>
<td>(0.60)</td>
<td></td>
<td></td>
<td>(0.89)</td>
</tr>
<tr>
<td><strong>ROA at filing</strong></td>
<td>-0.119</td>
<td>-0.119</td>
<td></td>
<td>-1.115</td>
</tr>
<tr>
<td></td>
<td>(-0.07)</td>
<td></td>
<td></td>
<td>(-0.44)</td>
</tr>
<tr>
<td><strong>Investment 2 years before filing</strong></td>
<td>-4.080</td>
<td>2.311</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.81)</td>
<td></td>
<td></td>
<td>(0.37)</td>
</tr>
<tr>
<td><strong>Size at emergence</strong></td>
<td>-0.039</td>
<td>0.028</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.09)</td>
<td></td>
<td></td>
<td>(0.08)</td>
</tr>
<tr>
<td><strong>Leverage at emergence</strong></td>
<td>0.511</td>
<td>0.511</td>
<td></td>
<td>0.593</td>
</tr>
<tr>
<td></td>
<td>(1.11)</td>
<td></td>
<td></td>
<td>(1.60)</td>
</tr>
<tr>
<td><strong>Current ratio at emergence</strong></td>
<td>-0.468</td>
<td>-0.609*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.51)</td>
<td></td>
<td></td>
<td>(-1.94)</td>
</tr>
<tr>
<td><strong>ROA at emergence</strong></td>
<td>-0.781</td>
<td>1.043</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.38)</td>
<td></td>
<td></td>
<td>(-0.42)</td>
</tr>
<tr>
<td><strong>Investment 1 year after Emergence</strong></td>
<td>10.188***</td>
<td>6.846***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.88)</td>
<td></td>
<td></td>
<td>(3.53)</td>
</tr>
<tr>
<td><strong>fee1:</strong></td>
<td>-6.766</td>
<td>-0.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Professional fees/Total assets at filing</strong></td>
<td></td>
<td></td>
<td></td>
<td>(-1.44)</td>
</tr>
<tr>
<td><strong>Prepack X fee1:</strong></td>
<td>35.777*</td>
<td></td>
<td></td>
<td>(-1.44)</td>
</tr>
<tr>
<td></td>
<td>(1.82)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Prepack X Investment before filing</strong></td>
<td></td>
<td></td>
<td></td>
<td>-11.398</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-1.44)</td>
</tr>
<tr>
<td><strong>Prepack X Investment after Emergence</strong></td>
<td></td>
<td></td>
<td></td>
<td>8.569</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(1.46)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>-1.595***</td>
<td>-1.331*</td>
<td>-1.955***</td>
<td>-1.507</td>
</tr>
<tr>
<td></td>
<td>(-6.52)</td>
<td>(-1.67)</td>
<td>(-3.52)</td>
<td>(-1.26)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>483</td>
<td>171</td>
<td>140</td>
<td>176</td>
</tr>
<tr>
<td><strong>Pseudo R-squared</strong></td>
<td>0.0130</td>
<td>0.118</td>
<td>0.0884</td>
<td>0.145</td>
</tr>
</tbody>
</table>
1.11 Online Appendix

“Patience is a virtue: Evidence from insolvency”

Guangqian Pan
Appendix A.1: Continuous model

At time 0, the realized value for the firm is $V_0$. At time $T$, the realized value of the firm $\tilde{V}_T$. Here, the long term true value for the firm is $\tilde{V} \sim N(u, \sigma_0^2)$. The realized value will convert to the true value in the long run if the process is frictionless. However, the reorganization process is costly and involves a variable cost $c$. Meanwhile, there will be noise related to the reorganization process. $\tilde{V}_T$ is characterized by a diffusion process as follows:

$$d\tilde{V}_T = \left[ \delta \ast (\tilde{V} - \tilde{V}_T - cT) - c \right] dt + \sigma dz_t$$

Then, we can write $\tilde{V}_T$ as the following equation:

$$\tilde{V}_T = e^{-\delta T} \ast V_0 + (1 - e^{-\delta T}) \ast \tilde{V} - cT + \sigma \ast e^{-\delta T} \ast \int_0^T e^{\delta t} dz_t$$

$$= e^{-\delta T} \ast (V_0 + (e^{\delta T} - 1) \ast \tilde{V}) + \sigma \ast \int_0^T e^{\delta t} dz_t - cT$$

Proof:

$$\frac{d\tilde{V}_T}{dT} = -\delta \ast e^{-\delta T} \ast \left( V_0 + (e^{\delta T} - 1) \ast \tilde{V} + \sigma \ast \int_0^T e^{\delta t} dz_t \right) + e^{-\delta T} \ast (\delta \ast e^{\delta T} \ast \tilde{V}) - c$$

$$= -\delta \ast (\tilde{V}_T + Tc) + \delta \ast \tilde{V} - c$$

$$\frac{d\tilde{V}_T}{dz_T} = \sigma \ast e^{-\delta T} \ast e^{\delta T} = \sigma$$

Use Ito’s lemma,

$$d\tilde{V}_t = (-\delta \ast (\tilde{V}_T + cT) + \delta \ast \tilde{V} - c) dt + \sigma dz_t = \left[ \delta \ast (\tilde{V} - \tilde{V}_T - cT) - c \right] dt + \sigma dz_t$$
Since the long term true value for the firm follows a normal distribution: \( \tilde{V} \sim N(\mu, \sigma_0^2) \). Then, \( \tilde{V}_t | \tilde{V}, \theta \sim N(e^{-\delta T} * V_0 + (1 - e^{-\delta T}) * \tilde{V} - t c \frac{\sigma^2}{2\delta} (1 - e^{-2\delta T})) \).

**Proof:**

\[
E(\tilde{V}_t | \tilde{V}, \theta) = E \left( e^{-\delta T} \left( V_0 + (e^{\delta T} - 1) * \tilde{V} + \sigma * \int_0^T e^{\delta t} \, dz_t \right) - c T \right) \tilde{V}, \theta) \\
= e^{-\delta T} \left( V_0 + (e^{\delta T} - 1) * \tilde{V} \right) - c T
\]

\[
\text{Var}(\tilde{V}_t | \tilde{V}, \theta) = \text{Var} \left( e^{-\delta T} \left( V_0 + (e^{\delta T} - 1) * \tilde{V} + \sigma * \int_0^T e^{\delta t} \, dz_t \right) - c T \right) \tilde{V}, \theta) \\
= \text{Var} \left( \sigma * \int_0^T e^{-\delta(T - t)} \, dz_t \right) \tilde{V}, \theta) = \sigma^2 * \text{Var} \left( e^{-\delta(T - t)} \, dz_t \right) \tilde{V}, \theta) \\
= \sigma^2 * \left[ E \left( \int_0^T e^{-2\delta(T - t)} \, dz^2_t \right) \tilde{V}, \theta) - \left( E \left( e^{-\delta(T - t)} \, dz_t \right) \tilde{V}, \theta) \right)^2 \right] \\
= \sigma^2 * E \left( \int_0^T e^{-2\delta(T - t)} \, dz^2_t \right) \tilde{V}, \theta) = \sigma^2 * \int_0^T e^{-2\delta(T - t)} \, dt \\
= \sigma^2 * e^{-2\delta T} \int_0^T e^{2\delta T} \, dt = \sigma^2 * \frac{e^{-2\delta T}}{2\delta} \left( e^{2\delta T} - 1 \right) = \frac{\sigma^2}{2\delta} (1 - e^{-2\delta T})
\]

Therefore, \( \tilde{V}_t | \tilde{V}, \theta \sim N(e^{-\delta T} * V_0 + (1 - e^{-\delta T}) * \tilde{V} - t c \frac{\sigma^2}{2\delta} (1 - e^{-2\delta T})) \).

Additionally,

\[
\tilde{V}_t | \theta \sim N(e^{-\delta T} * V_0 + (1 - e^{-\delta T}) * \mu - t c, (1 - e^{-\delta T})^2 * \sigma_0^2 + \frac{\sigma^2}{2\delta} (1 - e^{-2\delta T}))
\]

At a time point \( t \), creditors can use the Bayesian updating process to update their beliefs about the firm’s true value \( \tilde{V} \). The posterior probability \( p(\tilde{V} | \tilde{V}_t, \theta) \) follows a normal distribution and can be characterized as follows:
\[ p(\tilde{V}|\tilde{V}_t, \theta) \sim N \left( \frac{(1 - e^{-\delta t}) \cdot (tc + \tilde{V}_t - e^{-\delta t} \cdot V_0)}{\sigma^2 + (1 - 2\delta) + \frac{\mu}{\sigma_0^2}} \right) \]

\[ \times \left( \frac{(1 - e^{-\delta t})^2}{\sigma^2 + (1 - 2\delta) + \frac{\mu}{\sigma_0^2}} \right) \left( \frac{(1 - e^{-\delta t})^2}{\sigma^2 + (1 - 2\delta) + \frac{\mu}{\sigma_0^2}} \right)^{-1} \]

Proof:

\[ p(\tilde{V}|\tilde{V}_t, \theta) = \frac{p(\tilde{V}_t|\tilde{V}) \cdot p(\tilde{V}|\theta)}{p(\tilde{V}_t|\theta)} \propto p(\tilde{V}_t|\tilde{V}) \cdot p(\tilde{V}|\theta) \]

\[ p(\tilde{V}|\tilde{V}_t, \theta) \propto \exp \left( -\frac{(\tilde{V}_t - (e^{-\delta t} \cdot V_0 + (1 - e^{-\delta t}) \cdot \tilde{V} - tc))^2}{2\sigma^2 + (1 - 2\delta)} \right) \cdot \exp \left( -\frac{(\tilde{V} - \mu)^2}{2\sigma_0^2} \right) \]

\[ = \exp \left( -\frac{(\tilde{V}_t - (e^{-\delta t} \cdot V_0 + (1 - e^{-\delta t}) \cdot \tilde{V} - tc))^2}{2\sigma^2 + (1 - 2\delta)} \right) - \frac{(\tilde{V} - \mu)^2}{2\sigma_0^2} \]

\[ \propto \exp \left( -\frac{(1 - e^{-\delta t})^2 \cdot \tilde{V}^2 - 2\tilde{V} \cdot (1 - e^{-\delta t}) \cdot (tc + \tilde{V}_t - e^{-\delta t} \cdot V_0)}{2\sigma^2 + (1 - 2\delta)} \right) \]

\[ - \frac{\tilde{V}^2 - 2\tilde{V} \cdot \mu}{2\sigma_0^2} \]

\[ p(\tilde{V}|\tilde{V}_t, \theta) \sim N(\tilde{\mu}, s^2) \]

\[ p(\tilde{V}|\tilde{V}_t, \theta) \propto \exp \left( -\frac{\tilde{V}^2 - 2\tilde{V} \cdot \tilde{\mu}}{2s^2} \right) \]

\[ s^2 = \left( \frac{(1 - e^{-\delta t})^2}{\sigma^2 + (1 - 2\delta)} + \frac{1}{\sigma_0^2} \right)^{-1} \]
\[\tilde{u} = \left( \frac{(1 - e^{-\delta t}) \cdot (tc + \bar{V}_t - e^{-\delta t} \cdot V_0) + \mu}{\sigma^2} \right) \cdot s^2 \]

\[= \left( \frac{(1 - e^{-\delta t}) \cdot (tc + \bar{V}_t - e^{-\delta t} \cdot V_0) + \mu}{\sigma^2} \right) \cdot s^2 \cdot \left( \frac{(1 - e^{-\delta t})^2 + \frac{1}{\sigma_0^2}}{\gamma (1 - e^{-2\delta t})} \right)^{-1} \]

\[p(\bar{V}|\bar{V}_t, \theta) \sim N\left( \frac{(1 - e^{-\delta t}) \cdot (tc + \bar{V}_t - e^{-\delta t} \cdot V_0) + \mu}{\sigma^2} \right) \cdot s^2 \cdot \left( \frac{(1 - e^{-\delta t})^2 + \frac{1}{\sigma_0^2}}{\gamma (1 - e^{-2\delta t})} \right)^{-1} \]

Next, we explore a firm’s decision-making choice. A firm can either voluntarily liquidate or be forced into liquidation when a long run liquidation threshold \( L \) is triggered. A firm occurs a fixed liquidation cost \( C_L \) in the event of liquidation. At time \( t \), the firm realizes \( V_t \) and its corresponding conditional distribution for its true value \( \bar{V} \) as \( p(\bar{V}|V_t, \theta) \). The firm can either liquidate its assets or emerge from bankruptcy. If the firm liquidates right away, the payoff would be \( V_t - C_L \). If the firm emerges from the bankruptcy, its value depends on its realized long-term value \( \bar{V} \). If \( \bar{V} \leq L + tc \), the firm has to liquidate in the future and the payoff will be \( \bar{V} - tc - C_L \). If \( \bar{V} > L + tc \), the firm will continue and the payoff will be \( \bar{V} - tc \).

Overall, at time \( t \), a firm’s liquidation payoff is \( V_t - C_L \) and its emerge payoff is

\[\int_{-\infty}^{\bar{V}} p(\bar{V}|V_t, \theta) \cdot (\bar{V} - tc - C_L) \, d\bar{V} + \int_{\bar{V}}^{\infty} p(\bar{V}|V_t, \theta) \cdot (\bar{V} - tc) \, d\bar{V} = E(\bar{V}|V_t, \theta) - tc - C_L \cdot p(\bar{V} \leq L + tc|V_t, \theta) \]

The optimal payoff \( E_t \) will be

\[E_t = \max\{V_t - C_L, E(\bar{V}|V_t, \theta) - tc - C_L \cdot p(\bar{V} \leq L + tc|V_t, \theta)\} \]

At time 0, the expected optimal payoff will be a function of time \( t \):
$$f(t) = E_{V_t}(E_t) = E_{V_t}(\max\{V_t - C_L, E(\bar{V} | V_t, \theta) - t c - C_L * p(\bar{V} \leq L + t c | V_t, \theta)\}) \ .$$ Firms choose an optimal $t$ to maximize their expected payoff.
Table A.1

**Direct Costs of Traditional Chapter 11 and Prepack**

This table presents the direct costs of traditional Chapter 11 and prepacks. All cost measurements use the direct cost during the bankruptcy divided by the pre-bankruptcy total assets except Betker (1995). Betker (1995) uses the direct costs both before and during bankruptcy divided by the pre-bankruptcy total assets. All data are based on the U.S. Chapter 11 framework except Thorburn (2000), who uses a Swedish bankruptcy sample. Both means and medians are included in the table for cross-study comparison. The number of observations, data sources and sample periods are also included.

<table>
<thead>
<tr>
<th>Study</th>
<th>Traditional Mean</th>
<th>Median</th>
<th>Obs.</th>
<th>Prepack Mean</th>
<th>Median</th>
<th>Obs.</th>
<th>Data Source</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our finding</td>
<td>3.46%</td>
<td>2.65%</td>
<td>76</td>
<td>2.03%</td>
<td>1.67%</td>
<td>80</td>
<td>UCLA-LoPucki Bankruptcy Research Database (BRD)</td>
<td>1980–2014</td>
</tr>
<tr>
<td>Weiss (1990)</td>
<td>2.80%</td>
<td>2.50%</td>
<td>31</td>
<td>2.90%</td>
<td>2.60%</td>
<td>44</td>
<td>7 U.S. Bankruptcy Courts</td>
<td>1980–1986</td>
</tr>
<tr>
<td>Betker (1995)</td>
<td></td>
<td></td>
<td></td>
<td>2.60%</td>
<td></td>
<td></td>
<td>Multiple bankruptcy sources</td>
<td>1986–1993</td>
</tr>
<tr>
<td>Tashjian et al. (1996)</td>
<td>1.85%</td>
<td>1.45%</td>
<td>39</td>
<td></td>
<td></td>
<td></td>
<td>News search</td>
<td>1986–1993</td>
</tr>
<tr>
<td>Thorburn (2000)</td>
<td>6.40%</td>
<td>4.50%</td>
<td>210</td>
<td>2.50%</td>
<td>1.50%</td>
<td>53</td>
<td>Swedish Upplysnings Central AB's database</td>
<td>1988–1991</td>
</tr>
</tbody>
</table>
### Table A.2
Industry Prepack Rate and Emergence Rate

This table presents firms’ bankruptcy outcomes by industry. We separate the firms into nine industries by their SIC Division Code. The variable prepack is an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from traditional Chapter 11. Prepack % is the number of filing firms as a percentage of the total number of firms filing Chapter 11. The variable emerge is an indicator that equals 1 if a firm emerges from reorganization through Chapter 11 and 0 if it fails to emerge through Chapter 11. Emerge % is the number of firms emerging from reorganization as a percentage of the number of firms filing bankruptcy. Refile in 5% is the number of firms that refile bankruptcy within 5 years after the bankruptcy divided by the total number of firms that emerge from bankruptcy before 2010.

<table>
<thead>
<tr>
<th>SIC Division</th>
<th>Prepack = 0</th>
<th></th>
<th>Prepack = 1</th>
<th></th>
<th>Total</th>
<th></th>
<th>Prepack %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Emerge %</td>
<td>Refile in 5 years %</td>
<td>Total</td>
<td>Emerge %</td>
<td>Refile in 5 years %</td>
<td>Total</td>
<td></td>
</tr>
<tr>
<td>Agricultural Production Crops</td>
<td>50%</td>
<td>0%</td>
<td>2</td>
<td>100%</td>
<td>0%</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Mining</td>
<td>66%</td>
<td>13%</td>
<td>29</td>
<td>82%</td>
<td>25%</td>
<td>11</td>
<td>40</td>
</tr>
<tr>
<td>Construction</td>
<td>87%</td>
<td>0%</td>
<td>15</td>
<td>88%</td>
<td>33%</td>
<td>8</td>
<td>23</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>74%</td>
<td>16%</td>
<td>218</td>
<td>90%</td>
<td>29%</td>
<td>96</td>
<td>314</td>
</tr>
<tr>
<td>Transportation, Communications, Electric, and Gas</td>
<td>58%</td>
<td>12%</td>
<td>117</td>
<td>86%</td>
<td>14%</td>
<td>58</td>
<td>175</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>58%</td>
<td>0%</td>
<td>24</td>
<td>80%</td>
<td>0%</td>
<td>10</td>
<td>34</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>55%</td>
<td>34%</td>
<td>97</td>
<td>87%</td>
<td>56%</td>
<td>23</td>
<td>120</td>
</tr>
<tr>
<td>Finance, Insurance, and Real Estate</td>
<td>38%</td>
<td>10%</td>
<td>99</td>
<td>82%</td>
<td>0%</td>
<td>22</td>
<td>121</td>
</tr>
<tr>
<td>Services</td>
<td>60%</td>
<td>5%</td>
<td>78</td>
<td>90%</td>
<td>21%</td>
<td>51</td>
<td>129</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>61%</td>
<td>15%</td>
<td>679</td>
<td>88%</td>
<td>23%</td>
<td>280</td>
<td>959</td>
</tr>
</tbody>
</table>
Table A.3

Propensity Score Matching Results

The table presents the regression results for firms’ refiling ratios after propensity score matching. The dependent variable is firms’ refiling ratios. We examine the propensity to refile, defined as a firm that files a bankruptcy within 5 years after it emerges from a previous bankruptcy. Model (1) repeats the previous logistic regression after matching the firms under prepack and traditional Chapter 11 on all financial characteristics both at filing and at emergence. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from traditional Chapter 11. We control for a range of firm financial variables both at filing and at emergence: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is the total current assets as a percentage of the total current liabilities; Leverage is the total liabilities as a percentage of the total assets; and ROA is earnings before Interest and Tax (EBIT) as a percentage of the total assets. Model (2) calculates the average treatment effects using a propensity score matching regression. Model (3) calculates the average treatment effects using augmented inverse probability weighting. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

<table>
<thead>
<tr>
<th>Methods</th>
<th>(1) Matched sample logit</th>
<th>(2) Propensity score matching regression</th>
<th>(3) Augmented inverse probability weighting</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average Treatment Effects of Prepack</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prepack</td>
<td>1.102**</td>
<td>0.169*</td>
<td>0.166*</td>
</tr>
<tr>
<td></td>
<td>(2.54)</td>
<td>(1.72)</td>
<td>(1.84)</td>
</tr>
<tr>
<td>Size at filing</td>
<td>-0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>-0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>0.551***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.58)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA at filing</td>
<td>2.175</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size at Emerging</td>
<td>-0.095</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.20)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage at Emerging</td>
<td>0.939</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current ratio at Emerging</td>
<td>-0.151</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.51)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA at Emerging</td>
<td>-2.644</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.98)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.884***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>130</td>
<td>183</td>
<td>183</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.1155</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure A.1
Bankruptcy decisions with two types of claims.
Figure A.2
Bankruptcy decisions using a continuous model

Base Line Model

Different Variable Bankruptcy Costs

Different Noise

Different Risk

Legend:
- Low
- Medium
- High
Figure A.3: Refiling Rates Differ among the Various Variables.
Panel A: Court Locations vs Refile

Panel B: Industries vs Refile
Panel C: Judges vs Refile

Panel D: Leading DIP Attorney vs Refile
Table A.4: Robustness Check for the Refiling Ratio

The table presents the robustness check of the logistic regression results for firms’ refiling ratios. The dependent variable is firms’ emergence rate. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from traditional Chapter 11. We control for a range of firm financial variables at filing: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is the total current assets as a percentage of the total current liabilities; Leverage is total liabilities as a percentage of the total assets; and ROA is earnings before Interest and Tax (EBIT) as a percentage of the total assets. The surname of the bankruptcy judge first handling a case is included as a judge dummy for model (1). Model (2) includes variables related to court forum shopping. Forum shopping equals 1 if the firm’s bankruptcy court location is different from the firm’s headquarters location and 0 otherwise. Model (3) controls for industry fixed effects based on firms’ SIC Division. Model (4) controls for the DIP attorney handling the case. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***. We keep significant coefficients for judge dummies and attorney dummies.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Judge</th>
<th>(2) Court Shopping</th>
<th>(3) Industry FE</th>
<th>(4) Attorney FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepack</td>
<td>0.723***</td>
<td>0.638***</td>
<td>1.015**</td>
<td>0.815**</td>
</tr>
<tr>
<td></td>
<td>(4.09)</td>
<td>(2.65)</td>
<td>(2.32)</td>
<td>(2.47)</td>
</tr>
<tr>
<td>Size at filing</td>
<td>-0.287*</td>
<td>-0.282*</td>
<td>-0.359**</td>
<td>-0.365***</td>
</tr>
<tr>
<td></td>
<td>(-1.94)</td>
<td>(-1.83)</td>
<td>(-2.26)</td>
<td>(-3.63)</td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>-0.056</td>
<td>-0.001</td>
<td>-0.039</td>
<td>-0.106</td>
</tr>
<tr>
<td></td>
<td>(-0.14)</td>
<td>(-0.00)</td>
<td>(-0.09)</td>
<td>(-0.35)</td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>0.071</td>
<td>0.067</td>
<td>-0.041</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.57)</td>
<td>(0.51)</td>
<td>(-0.30)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>ROA at filing</td>
<td>1.060</td>
<td>0.946</td>
<td>0.587</td>
<td>1.060</td>
</tr>
<tr>
<td></td>
<td>(0.74)</td>
<td>(0.68)</td>
<td>(0.32)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>1. Judge Dummy Walsh</td>
<td>0.814*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.80)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Court Dummy Forum Shopping</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filed in Delaware</td>
<td>0.699</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filed in Manhattan</td>
<td>0.202</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Attorney Dummy Weilgotshal</td>
<td></td>
<td></td>
<td></td>
<td>0.629*</td>
</tr>
<tr>
<td></td>
<td>(1.75)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skaddenarps</td>
<td>1.287***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.15)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-1.648**</td>
<td>-1.704**</td>
<td>-2.363***</td>
<td>-1.499**</td>
</tr>
<tr>
<td></td>
<td>(-2.08)</td>
<td>(-2.05)</td>
<td>(-5.22)</td>
<td>(-2.16)</td>
</tr>
</tbody>
</table>

Judge Yes
Court Yes
Industry Yes
Attorney Yes
Observations 299 312 293 299
Pseudo R-squared 0.0724 0.0573 0.133 0.0785
Table A.5
Robustness Check for Emergence Rate

The table presents the robustness check of the logistic regression results for firms’ emergence rates. The dependent variable is firms’ emergence rate. The independent variable of interest is prepack: an indicator that equals 1 if a firm emerges from reorganization through pre-package or pre-negotiation and 0 if a firm emerges from traditional Chapter 11. We control for a range of firm financial variables at filing: Size is the log amount of a firm’s total assets in book value after adjusting for inflation; Current Ratio is the total current assets as a percentage of the total current liabilities; Leverage is the total liabilities as a percentage of the total assets; and ROA is earnings before Interest and Tax (EBIT) as a percentage of the total assets. The surname of the bankruptcy judge first handling a case is included as a judge dummy for model (1). Model (2) includes variables related to court forum shopping. Forum shopping equals 1 if the firm’s bankruptcy court location is different from the firm’s headquarters location and 0 otherwise. Model (3) controls for industry fixed effects based on firms’ SIC Division. Model (4) controls for the DIP Attorney handling the case. Robust t-statistics are shown in parentheses (with standard errors clustered by industry). Significance levels of 10, 5, and 1 percent are represented by *, **, and ***. We keep significant coefficients for judge dummies and attorney dummies.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Judge</th>
<th>(2) Court Shopping</th>
<th>(3) Industry FE</th>
<th>(4) Attorney FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepack</td>
<td>1.230***</td>
<td>1.223***</td>
<td>1.252***</td>
<td>1.107***</td>
</tr>
<tr>
<td></td>
<td>(4.29)</td>
<td>(4.07)</td>
<td>(4.08)</td>
<td>(4.10)</td>
</tr>
<tr>
<td>Size at filing</td>
<td>0.211***</td>
<td>0.215***</td>
<td>0.245***</td>
<td>0.206***</td>
</tr>
<tr>
<td></td>
<td>(4.32)</td>
<td>(4.80)</td>
<td>(3.01)</td>
<td>(3.81)</td>
</tr>
<tr>
<td>Leverage at filing</td>
<td>1.383***</td>
<td>1.319***</td>
<td>1.278***</td>
<td>1.330***</td>
</tr>
<tr>
<td></td>
<td>(5.10)</td>
<td>(4.87)</td>
<td>(4.00)</td>
<td>(4.97)</td>
</tr>
<tr>
<td>Current ratio at filing</td>
<td>-0.173***</td>
<td>-0.178***</td>
<td>-0.216**</td>
<td>-0.174***</td>
</tr>
<tr>
<td></td>
<td>(-3.18)</td>
<td>(-3.24)</td>
<td>(-2.32)</td>
<td>(-3.05)</td>
</tr>
<tr>
<td>ROA at filing</td>
<td>3.037***</td>
<td>2.968***</td>
<td>2.494***</td>
<td>3.018***</td>
</tr>
<tr>
<td></td>
<td>(6.40)</td>
<td>(5.68)</td>
<td>(3.07)</td>
<td>(5.22)</td>
</tr>
<tr>
<td>1. Judge Dummy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sontchi</td>
<td>-1.323***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.96)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Court Dummy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forum Shopping</td>
<td></td>
<td>-0.034</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filed in Delaware</td>
<td></td>
<td>-0.279</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.79)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filed in Manhattan</td>
<td></td>
<td>-0.031</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.07)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.468*</td>
<td>-0.321</td>
<td>-0.422</td>
<td>-0.451**</td>
</tr>
<tr>
<td></td>
<td>(-1.82)</td>
<td>(-1.07)</td>
<td>(-0.68)</td>
<td>(-2.10)</td>
</tr>
<tr>
<td>Judge</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Court</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIC Division</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attorney</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>544</td>
<td>544</td>
<td>544</td>
<td>544</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.133</td>
<td>0.117</td>
<td>0.142</td>
<td>0.124</td>
</tr>
</tbody>
</table>

96
2. Chapter 2: Risk Sharing, Creditor Diversity, and Bank Regulation
Risk Sharing, Creditor Diversity, and Bank Regulation

Kentaro Asai† Guangqian Pan‡

Abstract

We examine the effectiveness of bank regulation in the light of creditor diversity. We focus on a bank’s value generation through the interaction of its issuance of securities with different risk levels, matching between securities and creditors, and capital buffer. Our calibration and evidence suggest even a well-capitalized bank cannot eliminate financial fragility in the absence of creditor diversity. We find capital regulation is only effective when a bank can save financing costs by matching the riskiness of securities and the risk tolerance of diverse creditors. If financial fragility is persistent, we suggest liquidity regulation can mitigate excessive risk-taking.

*We benefited from discussions with Andrew Ainsworth (discussant), Antje Berndt, Philip Gharghori (discussant), Simon Grant, Kimie Harada, Jean Helwege, Yunzhi Hu, Anil Kashyap, Timothy Kam, Nobuhiro Kiyotaki, David Martinez-Miera, Casey Mulligan, Phong Ngo, Kazuhiko Ohashi, George Pennacchi, Takeshi Yamada, and Shang Jin Wei as well as feedbacks from Kentaro Asai’s advisors Ali Hortaçsu, Zhiguo He, and Gregor Matvos in his Public Lecture. We thank the conference and seminar participants at Econometric Society Australasian Meeting (2018), ANU RSFAS Summer Camp, Asian Finance Association (2018), FIRN Annual Conference (2018), New Zealand Finance Meeting (2018), Australian National University, and University of Sydney. We also thank Diego Puente Moncayo for research assistance.

†Address: 26C Kingsley Street Acton ACT 2601, Australia, e-mail: kentaro.asai@anu.edu.au.
‡Address: 26C Kingsley Street Acton ACT 2601, Australia, e-mail: guangqian.pan@anu.edu.au.
2.1 Introduction

Recently, bank regulators are proposing to further differentiate regulatory requirements by bank types. For example, Federal Deposit Insurance Corporation (FDIC) proposes a relief of strict capital regulation for banks with less than $10 billion in assets, most of which are community banks\(^1\). Because the majority of the U.S. banks are community banks with regional customer focus, this proposal is considered a large-scale deregulation of the U.S. banking sector. On the other hand, remaining large banks have been bearing higher capital requirements since the Global Financial Crisis (GFC).\(^2\) A similar asymmetric approach has been implemented for liquidity regulation. Unlike large banks, community banks are not subject to the current liquidity coverage ratio (LCR) and proposed net stable funding ratio (NSFR) requirements in the U.S. This asymmetric approach is reasonable to the extent that the two types of banks are different mainly in their systemic importance. However, the two types of banks seem different in other dimensions as well. In particular, community banks tend to be funded by less diverse creditors, owing to their geographical concentration in the deposit market, whereas large banks tend to be funded by more diverse creditors. The difference in creditor diversity is potentially a critical yet overlooked factor that needs to be taken into account, considering the most concentrated banks on the deposits are least regulated in current regulation regime. To assess the possibility for an alternative asymmetric scheme, we study the differential effects of bank regulations in the light of a bank’s diversification of creditors.

From our calibration and empirical analysis, we find, with lack of creditor diversity, even a well-

\(^2\) Indeed, FDIC Chairman Jelena McWilliams said, “Our largest, most systemically important banks would continue to be subject to the most rigorous standards, and their smaller, less systemically important peers would be subject to standards tailored to their risk profile.”
capitalized bank cannot eliminate its financial fragility. We then find capital regulation is only effective conditional on the presence of risk aversion heterogeneity among creditors. A well-capitalized bank can issue a sizable portion of safe securities along with risky ones, despite the risk of its assets. Then, its net worth becomes robust to adverse shocks when it can save financing costs by matching safe securities to the risk averse and risky ones to the risk tolerant in the presence of creditor diversity. However, if it cannot take advantage of this matching process, its net worth is insufficient for absorbing adverse shocks even in the presence of capital cushion. If financial fragility is persistent, we rather recommend liquidity regulation to mitigate excessive risk-taking. Consequently, we conclude capital regulation is more effective for large banks to mitigate their financial fragility, but less so for community banks. Meanwhile, we consider liquidity regulation can work as a substitute policy to mitigate excessive risk-taking for community banks.

Our analysis is based on a parsimonious model of financial intermediation that generates value through its risk-sharing role. In particular, we add to the model based on Leland (1998) and Hortaçsu et al. (2011) by allowing a bank to have a chance to save on financing costs through the issuance of safe securities. Because risk averse creditors demand less interest when they purchase safe securities while a bank can earn higher returns by investing in risky assets, the bank can generate positive net worth from this process. We however consider this process is imperfect given a bank cannot eliminate all risks on its assets through hedging and diversification (Stulz, 2014). If its assets remain risky, when it increases the issuance of safe securities, its remaining risky securities become riskier, because the loss incurred by each buyer of the risky securities increases at its failure. Credit spreads demanded by the buyers of the risky securities hence rise up in response to this move. In our model, a bank can still mitigate this pressure, to some extent, when bank capital serves as a cushion against asset losses, and hence increases liquidation value that can be seized by
creditors. If such cushion is available, a bank is able to issue a sizable volume of safe securities besides risky ones. As discussed below, when a bank issues securities with different risk levels, creditor diversity plays an important role in reducing financing costs.

When a bank issues two types of securities (safe and risky ones) with the help of bank capital, it attempts to minimize financing costs by matching the types of creditors with the types of securities it issues. In particular, if it is funded by creditors with diverse attitudes toward risk, it can match safe securities to the risk averse and risky ones to the risk tolerant, thereby reducing financing costs. This matching process hence makes its net worth large enough to absorb shocks to its financing costs and precludes financial panic. On the other hand, if it is funded by creditors with the same risk attitude, it pays larger financing costs because it cannot take advantage of this process. Then, a self-fulfilling financial crisis may occur, because the buyers of risky securities demand high spreads when they anticipate high risk whereas the bank’s net worth is too small for the bank to be solvent when the bank receives such adverse shocks. What is more, this crisis often accompanies excessive risk-taking, because a bank that is closer to default increases its risk appetites if it is protected by limited liability. Indeed, excessive risk-taking often coincides with financial crisis in reality. For example, in the US Savings and Loan Crisis during the 1980s, failed thrifts had disproportionately high concentrations of commercial mortgages, real estate loans, and direct equity investments (Barth et al., 1990). In the Japanese Banking Crisis during the 1990s, the Japanese banks passively took excessive risk by continuing lending to their most troubled borrowers (e.g., Peek and Rosengren (2005) and Caballero et al. (2008)). Researchers also suspect this coincidence is associated with recent crises in the US and Europe (e.g., Boyd and Hakenes (2014) and Drechsler et al. (2016)). In our model, however, liquidity requirement can still alleviate a bank’s excessive risk-taking even when a self-fulfilling financial crisis is possible, to some extent,
by forcing a bank to invest in fewer risky assets.

Overall, our model predicts capital regulation, which allows a bank to issue a sizable volume of safe securities besides risky ones, improves the bank’s solvency if the bank can utilize this matching process. The effect of capital regulation on bank stability is hence larger for the bank that is funded by creditors with diverse attitudes toward risk than for the bank that is funded by uniform depositors. This result suggests capital regulation becomes more effective when it is imposed on banks that diversify their creditors in terms of risk attitudes.

Our simulation results based on the calibrated model confirm our model predictions. In our simulations, at most two equilibria emerge: the safe equilibrium with the fewest risky assets and the lowest default risk, and, the high-risk equilibrium with the riskiest assets and the highest default risk. Then, we show the high-risk equilibrium can vanish if a bank is moderately capitalized and funded by creditors with heterogeneous risk preference. However, the high-risk equilibrium remains if either one of the above two conditions is unmet. This result suggests capital regulation is necessary for precluding financial fragility and only effective conditional on the presence of risk aversion heterogeneity among creditors.

Our simulation results also suggest liquidity regulation reduces a bank’s investment in risky assets though it cannot resolve multiple equilibria problem. Then, it has different welfare implications, depending on equilibrium type. In the safe equilibrium, the bank almost efficiently invests in risky assets in the laissez-faire condition, so this regulation causes underinvestment problem and reduces welfare. In the high-risk equilibrium, however, the bank tends to engage in excessive risk-taking in the laissez-faire condition, so this requirement can push down the bank’s risky assets to the near-efficient level. Liquidity regulation therefore could serve as a substitute policy, when capital regulation is absent or ineffective in mitigating financial fragility, as long as the
welfare loss in the safe equilibrium is limited.

We also conduct empirical analysis to see whether our model predictions are consistent with the evidence based on the U.S. bank holding companies (BHC) data. In this analysis, we measure creditors’ risk attitudes by collecting county-level demographic variables from the County Health Rankings & Roadmaps program. Among the available variables, we choose relevant proxies for risk preference based on implications from previous studies. After constructing the county-level risk preference index, we calculate the weighted standard deviation of each county’s risk preference index per bank, considering the bank’s deposits located in each county as the weight. Then, we use this variable as the measure of the bank’s risk aversion heterogeneity among creditors in our empirical analysis.

From this analysis, we find a bank’s interest expense rate is lower in the joint presence of risk-weighted capital ratio and creditors’ heterogeneous attitudes toward risk. Our model suggests a bank’s interest expense rate increases in the bank’s risky assets as well as default risk. This finding is therefore consistent with the prediction that the safe equilibrium, in which the bank issues more safe deposits and experiences fewer risky assets and lower default risk, is more likely to occur in the joint presence of them. However, we find the effect of risk aversion heterogeneity among creditors or bank capital on a bank’s interest expense rate is not statistically significant by itself. This result is consistent with our model prediction that the high-risk equilibrium is likely to exist in the absence of bank capital or risk aversion heterogeneity among creditors.

In summary, our study unveils the differential impact of capital regulation on bank stability, depending on the level of risk aversion heterogeneity among creditors. Banks without creditor diversity tend to be insensitive to capital regulation. Indeed, our simulations suggest multiple equilibria are likely to exist for those banks, regardless of whether they are well-capitalized or not.
Our simulations also suggest liquidity requirements can mitigate financial fragility for those banks, to some extent. Although liquidity requirements do not eliminate the presence of the high-risk equilibrium, these requirements still mitigate excessive risk-taking during the financial crisis. Consequently, imposing liquidity requirements can be welfare-enhancing when capital regulation is ineffective.

Our study mainly contributes to the recent policy debate on how to regulate community banks, but it also adds to the literature on the role of creditor heterogeneity in the banking system. In particular, we propose the alternative source of heterogeneity that raises bank value. For example, our work complements Gorton and Pennacchi (1990), who study the role of the joint presence of informed and uninformed creditors in a financial intermediary, by instead focusing on risk aversion heterogeneity among creditors.3

2.1.1 Institutional detail

Asymmetric banking regulations are widely seen between large banks and community banks. Large banks control the majority of total bank assets in the U.S. and the largest banks among them are generally considered systemically important in the domestic or global financial system. On the other hand, community banks account for 93 percent of all U.S. banks in number and 13 percent of total bank assets in 2015. These banks play important roles in providing finance to regional households and small businesses. In this section, we will discuss the features of the two types of banks and the asymmetry of capital and liquidity requirements between them.

2.1.1.1 Community banks

Traditionally, community banks are defined based on their size. Any bank with a total asset size

3 We note some previous research focuses on the risk preference of bank managers and owners instead of creditors (e.g., Sealey (1980); Ho and Saunders (1981)).
smaller than the indexed size threshold was defined as community bank. In 2012, FDIC introduced a broader definition of the community bank and included some bigger banks that focus on commercial bank activities with limited geographic operation. While small size is still an important feature for community banks, the recent definition change also emphasizes the geographic concentration of their operations. Community banks only operate within a maximum of 3 states or 2 metropolitan areas (MSA). Such regional focus of operation not only exposes these banks to similar risk factors on the asset side, but perhaps more importantly expose the banks to creditors with similar characteristics. In addition, community banks rely more on retail depositors than non-community banks given their limited access to the wholesale market. These two features bring us to rethink the importance of creditor diversity for community banks in the light of bank regulation.

2.1.1.2 Large banks

U.S. regulators categorize large banks into different groups based on their sizes and foreign exposures. For the purpose of capital requirement, banks are categorized into two groups: standardized approach banking organizations and advanced approaches banking organizations. Standardized approach banking organizations have total consolidated assets of less than 250 billion dollars but more than 100 billion dollars and total on-balance sheet foreign exposure of less than 10 billion dollars. Advanced approaches banking organizations includes bank organizations with 250 billion dollars or more in total consolidated assets or 10 billion dollars or more in total on-balance sheet foreign exposure. Within advanced approach banking organizations, bank holding companies with more than 700 billion dollars in total consolidated assets or more than 10 trillion dollars in total assets under custody and Globally systemically important banks (GSIBs) and their subsidiaries are subject to additional regulatory requirements. For the purpose of liquidity requirement, banks are categorized into two similar groups with different thresholds.
2.1.1.3 Asymmetric banking regulation

After the GFC, numerous banking regulations have been introduced to enhance the financial stability of the banking industry. In particular, Basel III introduced both new capital regulation requirements and liquidity regulation frameworks. Nevertheless, these regulations were implemented very differently between large banks and community banks. Regarding capital regulation, largest banks are subject to a more complex regulation framework including both standardized and internal models-based capital regulation, supplementary leverage ratio and capital requirement buffers. On the other hand, community banks enjoyed the least stringent capital regulation among all banks. In addition, recent deregulation from regulators has simplified the capital regulation framework for community banks. Unlike the Basel III capital regulation framework with multiple capital requirements ratios, certain qualified community banks only need to meet one single leverage ratio: community bank leverage ratio (CBLR).

Regarding liquidity regulation, the current Liquidity Coverage Ratio (LCR) requirement and the proposed Net Stable Funding Ratio (NSFR) requirement are not applicable to banks with a total assets size smaller than 10 billion dollars (mostly community banks). For large banks, full LCR or a less stringent modified LCR are applied based on their sizes and foreign exposures.

In conclusion, banking regulation becomes divergent among banks. While lots of banking regulations have been put into act for large banks, community banks with homogeneous creditor exposures are largely under-regulated in the current framework. Our work serves to re-examine such asymmetric framework in the light of creditor diversity.

2.2 Relation to the literature

Our work is related to the current discussion on the role of financial intermediaries. The banking
literature has proposed three theories on the role of financial intermediaries: risk sharing, delegated monitoring, and liquidity provision. The first theory posits a bank transfers investment risk from risk-averse households to itself by issuing safe deposits – optimal risk sharing is facilitated by this transfer (e.g., Allen and Gale (1997)). The second theory suggests the role of a financial intermediary is to monitor investments on behalf of households, save on investment costs, and increase the credit supply (e.g., Diamond (1984); Martinez-Miera and Repullo (2017)). The third theory explores the synergy between a bank’s lending via credit lines and issuing deposits. Kashyap et al. (2002) argue the cost of holding liquid assets is lower when one institution specializes in both functions than when two separate institutions specialize in only one of the two functions; the two activities can “share” the burden of holding liquid assets, so that a bank that offers both deposits and loan commitments can reduce the volume of liquid assets. In this case, a bank is considered an institution that specializes in providing liquidity to the rest of the economy. Empirically, the discussion has not reached a consensus. For instance, Berger and Bouwman (2009) use a large sample of U.S. banks to construct four liquidity-creation measures, and they find bank liquidity creation is positively related to bank value. Their finding supports the third theory on banks’ liquidity-provision role. By contrast, Egan et al. (2017b) test the three theories and find the risk-sharing role is dominant because safe deposit productivity explains most of the variations in bank value. Our work contributes to the literature by showing that the strength of a bank’s risk-sharing role depends on the extent of risk aversion heterogeneity among creditors.

Another insight our analysis offers concerns the efficiency of capital regulation. Discussion on this topic has lasted a few decades but has not reached a consensus. Most studies find capital regulation is, at best, suboptimal. Capital regulations are proposed to mitigate excessive bank risk in the presence of limited liability and deposit insurance, as discussed in Merton (1977) and Sharpe
(1978). However, they are often criticized for their reduction of liquidity provision (Diamond and Rajan, 2000), bank lending (Thakor, 1996), and the crowding out of deposits (Gorton and Winton, 2017). Moreover, recent studies suggest banks might bypass capital regulations (e.g., Kisin and Manela (2016)). If regulatory arbitrage is possible, capital regulations might encourage banks to shift their risky lending practices into shadow banking (Plantin, 2014) or simply shift investments into risky projects within the same asset class (Duchin and Sosyura, 2014). Nevertheless, some studies suggest the necessity of capital regulation. For example, Morrison and White (2005) find capital regulation is an efficient tool enabling regulators to combat moral hazard and enhance screening outcomes. Mehran and Thakor (2011) show both theoretically and empirically that bank values are positively correlated with equity capital. The empirical findings about the effects of capital requirements are also mixed. Opponents of capital regulation argue it is costly for banks and society (e.g., Baker and Wurgler (2015); Kisin and Manela (2016); Van den Heuvel (2008)), reduces bank lending (Aiyar et al., 2014), and fails to reduce risk (Rime, 2001). Others find the effects of capital requirements are conditional. Berger and Bouwman (2009) test the relationship between capital and liquidity creation and find it tends to be positive for large banks and negative for small ones. Others find the effects of capital regulations depend on ownership structure (Laeven and Levine, 2009) or economic condition (Demirgüç-Kunt et al., 2013). We contribute to the ongoing discussion on the effects of capital regulation by showing they depend on the presence or absence of risk aversion heterogeneity among bank creditors.

Our study is also related to the literature on the differential behavior of heterogeneous investors toward a bank’s financial fragility. For example, Schmidt et al. (2016) suggest informed investors are more prone to run than uninformed investors, observing the differential withdrawals from the U.S. money market by investors with different monitoring abilities during the Global Financial
Crisis (GFC). Moreover, many studies show depositors deeply connected to banks are less prone to run, regardless of the banks’ fragility (e.g., Brown et al. (2013); Iyer et al. (2016); Iyer and Puri (2012)). Overall, these studies suggest heterogeneity in depositors’ characteristics substantially explains the diversity in their “ex-post” actions in the face of financial fragility (i.e., propensity to run). We complement those studies by instead focusing on their “ex-ante” actions – we analyze the selection of depositors with heterogeneous risk aversion into bank-issued securities with various risk levels.

Finally, our study is related to a growing body of literature on the role of risk aversion heterogeneity in finance. Empirical researchers have observed cross-sectional differences in risk tolerance (e.g., Barsky et al. (1997)). Many attribute such diversity to genetic variation (e.g., Barnea et al. (2010); Cronqvist and Siegel (2015)). On the other hand, Calvet and Sodini (2014), using data on Swedish twins to control for genetic differences, find environmental factors such as financial wealth, human capital, internal habits, and expenditure commitment can also affect risk preference. Risk aversion heterogeneity has been increasingly examined to explain various issues in asset pricing (e.g., Gârleanu and Panageas (2015)), investor decisions (e.g., Barnea et al. (2010); Cesarini et al. (2010); Cronqvist and Siegel (2015)), and wealth inequality (e.g., Gomez (2016)). We instead explore how bank creditors’ heterogeneous risk aversion affects their choices of bank-issued securities and the financial (in)stability of a bank.

2.3 Model

2.3.1 Overview

We consider banks that are spatially or segmentally separated and hence do not compete for deposits. Treating the bank as monopolist simplifies the analysis by allowing us to sidestep some complications that arise from having to model the deposit market equilibrium (Diamond and
Kashyap, 2016). Alternatively, the model can be interpreted as a description of the whole banking sector.

A monopolistic risk-neutral bank raises funds from both a continuum of creditors and itself to invest in risky and safe assets. We denote the fraction of risky assets by $q$ ($0 < q < 1$). Without loss of generality, we set the book value of the bank’s assets to 1. Specifically, the bank issues safe and risky securities to raise $1 - e(q)$ and self-funds $e(q)$ to meet the exogenous capital requirement ($0 \leq e(q) < 1$), where $e(.)$ is a differentiable function of $q$.\(^4\) We consider the cost of capital is $\gamma$ ($\gamma \geq 0$). For convenience, we use “demand deposits” as a generic term for safe securities, and “time deposits” as a generic term for risky securities.\(^5\)

[Insert Figure 1]

We assume the demand deposits can be withdrawn in the middle of the year, whereas the time deposits reach maturity at the end of the year. A fraction $y$ of the deposits are the demand deposits ($0 \leq y \leq 1$). Some of the demand deposits are withdrawn in the middle of the year when the bank survives. All of the demand deposits are withdrawn in the middle of the year when the bank defaults. The demand depositors rush into the bank to receive their claims before the time depositors receive their claims at the end of the year. Thus, the demand deposits are safe and senior, whereas the time deposits are risky and junior.

After the bank’s risky assets reach maturity at the end of the year, the bank consumes any positive residual claim as dividends after retaining some cash to recover its capital. Then, the bank continues business. Otherwise, the bank can inject equity to pay the net cash outflow and recover its capital

\(^4\) As seen later, $q$ is defined as the fraction of risky assets of the bank’s total assets, which can be considered the bank’s risk-weighted assets (RWA). We consider the capital requirement can be sensitive to RWA.

\(^5\) Depending on the context, the demand deposits can be considered as insured deposits for which the banking sector self-reserves liquid assets. Correspondingly, we can consider the time deposits as generic short-term debts uninsured by the banking sector.
to continue business, or it can default voluntarily if it finds the amount of equity injection is greater than its charter value. Because of this possibility, the bank is subject to default risk. At default, the bank loses its capital because all the liquidation value is considered to be claimed by the depositors. We assume equity injection is possible only at the end of the year. Figure 1 describes the bank’s balance sheet and the actions of the bank’s stakeholders.

2.3.2 Timing

We develop an infinite-horizon model of banking. We consider the same series of events occurs in each year. These events are recursive for a surviving bank. We summarize these events occurring in each year as follows.

1. **Liability side**: Each depositor receives a unit endowment. The bank issues the demand and time deposits and posts the deposit rates. The depositors make investment decisions, and the bank finances itself to meet the capital requirement.

   **Asset side**: The bank invests in risky and safe assets.

2. **Liability side**: Some of the depositors receive private preference shocks. Observing the return to the bank’s risky assets, the bank makes a default decision.

   - **Default**: All the demand depositors withdraw their accounts.
   - **Survival**: The demand depositors who receive shocks withdraw their accounts.

   **Asset side**: The return on the bank’s risky assets is revealed to the bank.

   - **Default**: The bank liquidates all its risky assets to pay the principal of the deposits.\(^6\)

---

\(^6\) Because the bank can at worst lose its capital and pay the cost of capital after knowing the return to assets, whereas it inevitably does so when it chooses liquidation before knowing the return to the assets, it is always willing to avoid liquidation before knowing the return to assets. Therefore, the bank has an incentive to comply with this constraint.
• **Survival**: The bank uses the safe assets to cover the withdrawal of the demand deposits.

3. **Liability side**: The time deposits reach maturity. At survival, the bank receives dividends or injects equity.

• **Default**: The bank does not incur any further cash outflow due to limited liability, but it loses its capital and pays the cost of capital. Then a new business starts from Step 1.

• **Survival**: If the net cash outflow is negative or the bank loses some capital, the bank injects equity. Otherwise, the bank retains some of the net cash inflow to meet the capital requirement in the next period and consumes the rest as dividends. Then the business restarts from Step 1.

**Asset side**: At survival, the bank’s risky assets reach maturity.

• **Default**: The time depositors claim all the residual liquidation value. Then, the new business starts from Step 1.

• **Survival**: The bank uses the return to its risky assets and the residual safe assets to pay interest and principal to the time depositors, principal to the remaining demand depositors, and the cost of capital. Then, the business restarts from Step 1.

Figure 2 describes the life cycle of a bank in our model.

[Insert Figure 2]

2.3.3 Key frictions

2.3.3.1 Limited commitment and multiple equilibria

We assume the bank cannot commit to its risk choice to the depositors. This assumption is relevant to the financial contract between the bank and the depositors, because the bank, in principle, makes
investment and default decisions *after* the depositors lend their money to the bank. Although the depositors are probably able to anticipate the bank’s risk correctly, they are likely to incur a large cost to verify it. Given that they are often individuals or decentralized institutions, they are unlikely to afford the verification of the bank’s risk ex post. Then, any commitment of the bank’s risk choice seems incredible for the depositors. In the presence of this friction, the bank cannot control the depositors’ beliefs about its risk.

Under this constraint, the bank’s risky assets and default risk can jump up or down even if the bank’s fundamentals are left intact. For example, suppose the depositors suddenly anticipate more risky assets and larger default risk and raise credit spreads. Then the bank loses continuation value and has a reduced incentive to continue in business. When a bank is reluctant to continue in business, it has an increased risk-shifting incentive, raising both its risky assets and default risk. This closed feedback is a self-fulfilling prophecy mechanism that can cause financial instability. In other words, the banking system is subject to multiple equilibria, including high-risk equilibrium with high risky assets and default risk and safe equilibrium with low risky assets and default risk.

We, however, assume the bank commits to its investment decision to the government, because the government seems able to incur the cost to verify the bank’s asset risk ex post. This assumption becomes important in the presence of risk-sensitive regulation. For example, under this assumption, the bank internalizes the cost of risk taking that is imposed by the government through risk-sensitive capital requirement. In other words, we assume there is a “skin in the game” that provides the regulated bank with incentives to control risk.

2.3.3.2 Liquidation value constraint

We also consider the bank’s liquidation value perceived by the depositors has to be no lower than the amount of demand deposits. Owing to this constraint, the demand deposits become safe from
credit risks.

2.3.3.3 Liquidity constraint

In addition, we consider the bank is subject to a liquidity constraint. Because the bank can inject equity or receive investment returns from its risky assets only at the end of the year, it must have safe assets in amounts no lower than the size of the demand deposit withdrawal in the middle of the year. Alternatively, this constraint can be artificially imposed by a regulator as a liquidity requirement. In this case, the constraint may require a safe asset amount higher than the amount of the deposit withdrawal in the middle of the year.

2.3.4 The bank’s risk choice

We start from characterizing a bank’s risk choice to find equilibria. The bank determines (1) the asset risk through its investment decision in Step 1 and (2) the default risk through its default decision in Step 2.

For (1), we allow the bank to invest in either risky or safe assets. Recall $q$ is the exposure to risky loans. Then they invest $1 - q$ of the bank assets into safe assets, which does not yield any return. The return on risky assets is assumed to follow a normal distribution, $\mu + \sigma \tilde{Z} \sim N[\mu, \sigma^2]$ ($\sigma > 0$), where $\tilde{Z}$ follows the standard normal distribution i.i.d. across years. Then the bank’s return on assets, $\tilde{R}$, is represented by $\tilde{R} = q(\mu + \sigma \tilde{Z})$. Throughout the paper, we use $\Phi(.)$ and $\phi(.)$ to denote the CDF and PDF of a standard normal distribution, respectively. We denote $\phi(.)/(1 - \Phi(.))$ by $\lambda(.)$. We also consider the bank incurs the quadratic cost of risk taking, $\frac{k}{2} q^2$ ($k > 0$). The quadratic cost can be explained as the monitoring cost associated with
risk-taking behavior.\textsuperscript{7}

Regarding (2), Hortaçsu et al. (2011) show a firm plans the reservation rate of ROA to make an optimal default decision. Let the reservation rate be $R = q(\mu + \sigma z)$, such that the bank continues to operate if $\bar{R} \geq R$; otherwise, it liquidates its risky assets. Then, this strategy is equivalent to the strategy such that the bank continues as long as $\bar{z} \geq z$. We represent the default decision of the bank by $z$ because it sufficiently represents the probability of default ($\Phi(z)$). In this way, the bank optimizes both the asset risk $q$ (investment decision) and default risk $z$ (default decision). We denote the strategy of the bank by $s$, where $s = (q,z)$.

2.3.5 The depositors’ investment choice and the bank’s pricing strategy

Next, we characterize the depositors’ investment choice and the bank’s pricing strategy in Step 1. We consider every depositor has access to the financial market, where the depositor can invest in storage, which is safe and liquid, and riskless bond, which is safe but illiquid, in Step 1. Depositors who invest in storage can withdraw the funds in the middle of the year. No investment return to storage occurs, even if the depositor waits until the end of the year. On the other hand, depositors who invest in riskless bonds cannot withdraw the funds in the middle of the year. Instead, they receive a liquidity premium, $r$, in addition to the principal at the end of the year ($r \geq 0$), so that they are indifferent between these two securities in Step 1. Because they do not perceive their private preference shocks in Step 1, $r$ is independent of whether they receive preference shocks in Step 2.

These two securities are considered the depositors’ outside options. Then the supply of each type of deposits is perfectly elastic at the deposit rate that yields the same expected surplus as the

\textsuperscript{7} Jensen and Meckling (1976) also introduce the term for the monitoring cost of investment.
corresponding outside option. If the depositor is not worse off by investing in the deposits than by taking the outside option with the corresponding maturity, the depositor is incentive-compatible with investing in any amount of the deposits. The bank sets the optimal deposit rates that maximize its value while fulfilling the depositor’s incentive to fund the bank.

We consider depositors have two risk aversion levels. We call the more risk-averse ones “type h depositors” and the less risk-averse ones “type l depositors.” We denote the fraction of type h depositors as \(p (0 \leq p \leq 1)\). We also assume a fraction, \(x\), of the depositors receives private preference shocks in Step 2 independently of their type or the bank’s asset return \((0 \leq x)\). Hence, the aggregate withdrawal demand in Step 2 is predetermined.

To simplify our analysis, we assume the bank acquires funds from all the depositors. This assumption is relevant, for example, when the bank does not want to reduce the asset size for fear of losing systemic importance. Alternatively, when the regulator prefers the bank’s investment to the depositors’ self-investment due to the bank’s superior capacity of managing and monitoring assets, the regulator may mandate the bank to attract all the depositors.

For the rest of the section, we characterize the optimal deposit rates. We note the optimal demand deposit rate is zero because every depositor is willing to invest in the demand deposit as long as it is as beneficial as storage. Because the demand deposit is safe, the depositor is incentive-compatible with investing in it even if its rate is zero regardless of risk aversion type or whether the depositor receives preference shocks in Step 2.

---

8 For a positive analysis, \(x\) should be smaller than 1. For a normative analysis, as conducted later, this parameter can exceed 1. For example, if the regulator requires the bank to have safe assets equivalent to twice the amount of the demand deposits, \(x\) can be considered 2.

9 By being systemically important, the bank becomes fully capable of injecting equity thanks to financial support from the government that has an incentive to save systemically important banks.
Because the time deposit is risky while the demand deposit is safe, the deposits issued by the bank attract investors with different risk aversion levels. Although both depositors accept the bank’s offer of any non-negative demand deposit rate, type \( l \) depositors are more likely than type \( h \) depositors to accept the offer of the same time deposit rate. If the issued demand deposits, \( y \), are equal to or greater than the fraction of type \( h \) depositors, \( p \), the bank makes only type \( l \) depositors invest in the time deposits by setting the time deposit rate to the level at which type \( l \) depositors are indifferent between time deposits and outside options. In this way, the bank saves on the relatively high-risk premium it would pay if type \( h \) depositors (instead of type \( l \) depositors) invested in the time deposits.\(^{10}\) Correspondingly, the “marginal” time depositor type, \( f(y) \), becomes \( l \). On the other hand, if \( y \) is below \( p \), type \( h \) depositors also invest in the time deposits. Then, \( f(y) \) becomes \( h \) because type \( h \) depositors require a higher risk premium than type \( l \) depositors do. In this case, the bank sets the time deposit rate to the level at which type \( h \) depositors are indifferent between time deposits and outside options.\(^{11}\) Thus, the optimal time deposit rate set by the bank depends on the type of “marginal” time depositors, \( f(y) \).

Because the time deposit is risky and the bank’s risk is not verifiable for the depositors, the optimal time deposit rate also depends on the depositors’ common belief about the bank’s strategy, denoted \( s^d (s^d = (q^d, z^d)) \), where \( q^d \) is the belief about \( q \) and \( z^d \) is the belief about \( z \).\(^{12}\) We

---

\(^{10}\) If demand deposit rates are set to the level at which each of depositor is indifferent between demand deposits and outside options, whereas time deposit rates are set to the level at which type \( l \) depositors are indifferent between time deposits and outside options, type \( h \) depositors are indifferent between demand deposits and outside options and prefer demand deposits to time deposits, whereas type \( l \) depositors are indifferent between time deposits, demand deposits, and outside options. Then, type \( l \) depositors can be matched to both deposits, whereas type \( h \) depositors can be matched to only demand deposits.

\(^{11}\) If demand deposit rates are set to the level at which each depositor is indifferent between demand deposits and outside options, whereas time deposit rates are set to the level at which type \( h \) depositors are indifferent between time deposits and outside options, type \( l \) depositors prefer time deposits to demand deposits and outside options, whereas type \( h \) depositors are indifferent between time deposits, demand deposits, and outside options. Then type \( l \) depositors are matched to time deposits, whereas type \( h \) depositors can be matched to both deposits.

\(^{12}\) \( y \) is determined before the bank sets the deposit rates, so its decision is committable to the depositors by nature.
also denote the belief about the bank’s capital $e(q^d)$, which is a function of the belief about the bank’s risk weighted assets ($q^d$). We consider the optimal time deposit rate depends on $q^d$ as well as $z^d$, given that the portion of risky assets matters to the liquidation value of the bank. We assume the bank cannot sell its risky assets at book value, because the buyer has to incur the cost of default, probably, due to the difficulty of re-deploying the relationship lender.\(^{13}\) Consequently, the liquidation value of the bank’s risky assets is impaired. We denote the loss given default (LGD) of the bank’s risky assets as $d$, whereas the LGD of the bank’s safe assets is zero.

The time depositors compare the expected utility (EU) of investing in the time deposits with the EU of investing in riskless bonds, which have the same maturity as the time deposits in Step 1. The optimal time deposit rate, $i(y, s^d)$, is set to the level at which the marginal time depositors are indifferent between investing in the time deposits and riskless bond. Considering that the time depositors’ wealth in Step 3 is the payoff from their investment, $i(y, s^d)$ solves:

$$i(y, s^d) = \min \left\{ \left[ (1 - \Phi(z^d))U_f(y)(1 + i) + \Phi(z^d)U_f(y) \left( \frac{1 - dq^d - (1 - e(q^d))y}{(1 - e(q^d))(1 - y)} \right) \right] \geq U_f(y)(1 + r) \right\},$$

where $U_F(y)(.)$ is the utility function for the marginal time depositor’s type, $f(y)$.

2.3.6 The bank’s issuance of demand deposits

Finally, we note the bank chooses the level of demand deposits $y$, subject to the liquidation value constraint in Step 1.

\(^{13}\) Alternatively, the bank may not be able to find a third-party bidder who can manage the assets as efficiently as it can in a short time.
Given \( y \), the bank’s financing cost is

\[
c(y, s, s^d) = (1 - e(q))(1 - y)i(y, s^d),
\]

where \( (1 - y)i(y, s^d) \) is the bank’s interest expense rate.

2.3.7 Equilibrium

Based on our settings, a bank’s value, \( V(y, s, s^d) \), immediately after raising the deposits and the capital is described by

\[
V(y, s, s^d) = \frac{1 - \Phi(z)}{1 + r} E \left[ \begin{array}{c}
\text{survival probability} \\
\text{asset return} \\
\text{default probability} \\
\text{capital loss at default} \\
\text{capital cost}
\end{array} \right] - \frac{1 - \Phi(z)}{1 + r} \left( \begin{array}{c}
\text{expected asset return at survival} \\
\text{expected residual claim at survival} \\
\text{default probability} \\
\text{capital loss at default} \\
\text{capital cost}
\end{array} \right)
\]

We focus on the stationary Nash equilibrium in which the bank chooses the same strategy every year to maximize the continuation value, whereas the depositors rationally expect a stationary strategy from the bank. We denote the risk space of the bank by \( \Sigma \), where \( \Sigma = (0, 1) \times (-\infty, \tilde{z}) \). Then we define the equilibrium as follows:

---

14 Because of the property of normal distribution, \( E[\tilde{z} | \tilde{z} > z] = \mu + \frac{\Phi(z)}{1 - \Phi(z)} = \mu + \lambda(z) \). See Maddala (1983), for example.

15 We choose an open interval for the space of asset and default risks to focus on an interior solution in which \( (q, z) \) does not hit the corner of the interval. This approach enables us to simplify the computation of an equilibrium. The
**Definition 1.** Bank risk $s^*$ is the equilibrium if $(y^*, s^*) \in \arg\max_{(y,s)\in[0,1] \times S} V(y, s, s^*)$, s.t.

\[
1 - dq^* \geq (1 - e(q^*))y,
\]

liquidation value $\geq$ the amount of the demand deposits, perceived by the depositors

\[
1 - q \geq x(1 - e(q))y,
\]
safe assets $\geq$ the withdrawal of the demand deposits in Step 2

The first constraint captures the liquidation value constraint, whereas the second constraint captures the liquidity constraint. The last constraint reflects the regulation related to bank charter.

Then we provide the necessary condition for an equilibrium as follows: \(^\text{16}\)

**Proposition 1.** If $s^*$ is the equilibrium, it satisfies either

\[
\mu + \frac{\sigma \lambda(z^*)}{1 + r} \left[ (1 - y^*)i(y^*, s^*) - \Phi(z^*) \frac{\gamma}{1 - \Phi(z^*)} \right] = \frac{kq^*}{1 + r},
\]
marginal cost of risk taking

\[
gain from risk shifting + gain from rising capital
\]

\[
\frac{q^* \sigma (1 - \Phi(z^*)) (\lambda(z^*) - z^*)}{1 + r} - \frac{(1 + \gamma) e(q^*)}{1 + r} = V(y^*, s^*, s^*),
\]
opportunity cost of default

\[
y^* \in \arg\min_{y \in [0,1]} (1 - y)i(y, s^*) \text{ s.t. } 1 - dq^* \geq (1 - e(q^*))y,
\]

Or

---

\(^{16}\) In practice, numerically checking the optimality of the bank’s control variables is required.
Proof. See the appendix A.1.1.

This proposition suggests the bank chooses the asset risk such that the marginal net gain from risk taking through increases in expected asset returns, risk-shifting benefits, and capital is equal to the marginal cost from increases in operating expenses at equilibrium. It also optimally trades off charter value with the burden of injecting equity when setting the default threshold at equilibrium. However, when the liquidity constraint binds, the bank cannot freely determine asset risk. Therefore, the liquidity constraint may limit the bank’s endogenous choice of asset risk.

2.3.8 Key channel for achieving financial stability

We argue capital requirement is only effective conditional on the presence of risk aversion heterogeneity among creditors. To see why, we focus on how the capitalized bank’s default decision is determined at equilibrium, depending on the presence or absence of risk aversion heterogeneity among creditors. In particular, we analyze how the capitalized bank takes advantage of matching security and creditor types and reduces its financing cost in order to mitigate financial fragility.

We simplify our model for a moment to make our argument easier. Specifically, we fix asset risk \( q^* = q_0 \) where \( 0 < q_0 < 1 \), set the cost of capital equal to the risk-free rate \( (\gamma = r) \), and exclude liquidity requirement \( (x = 0) \). In addition, we assume linear risk-weighted capital requirement \( (e(q_0) = bq_0) \). Although this modification simplifies our model, it still clarifies the
key channel through which the bank achieves financial stability.

Under this condition, Proposition 1 implies equilibrium default risk is determined by the following equation:  

$$\frac{r + \Phi(z^*)}{1 + r} - q_0\sigma(z^* - z^*) = q_0(\mu + \sigma z^*) - c\left(y(q_0, z^*), (q_0, z^*), (q_0, z^*)\right) - \frac{k}{2}q_0,$$

where \(y(q_0, z)\) is the optimal fraction of demand deposits given \((q_0, z)\). The left-hand-side of the equation is the value of default that is converted into the corresponding flow item whereas the right-hand-side of the equation is the residual claim, that is, the opportunity cost of default. Equilibrium default risks are the intersections of the two curves.

The value of default diverges to \(\infty\) as \(z\to-\infty\) and converges to 0 as \(z\to+\infty\). This result reflects the intuition that the amount of equity injection required for bank survival on the margin is largest (smallest) when the bank’s default risk is smallest (largest) and hence the bank absorbs largest (smallest) asset losses on the margin. It, however, does not decrease in default risk monotonically. When default risk rises, shareholders require higher returns, raising the amount of equity injection required for bank survival.

The presence of the high-risk equilibrium depends on whether the opportunity cost of default is sufficiently large when default risk is high. The bank’s financing cost under the condition that creditors rationally anticipate the bank’s risk as assumed in equilibrium, \(c(y(q_0, z), (q_0, z), (q_0, z))\), increases in default risk \(z\), and the expected return conditional on

\[17\] In the appendix, we describe how we obtain this condition.
survival $q_0(\mu + \sigma \lambda(z))$ increases in $z$ as well.\footnote{$\lambda(z)$ is strictly increasing in $z$ because it is equal to the expectation of standard normal distribution truncated below by zero. Indeed, $\lambda(z) = E[\hat{z}|\hat{z} > z]$ where $\hat{z}$ follows standard normal distribution.} If the increase in financing cost far outweighs the increase in expected return conditional on survival, the opportunity cost of default can be small when default risk is high and hence intersects with the value of default there. However, if the bank’s financing cost does not increase in default risk so much, the bank’s opportunity cost of default is large enough to be above the value of default when default risk is high, meaning that choosing high default risk is costly for the bank. Under this condition, the bank’s net worth is robust to absorb adverse financing shocks. The key factor that mitigates an increase in financing cost is the risk tolerance of marginal time depositors. If marginal time depositors are risk tolerant enough, they do not require high risk premium even if they anticipate high default risk, reducing the bank’s financing cost when default risk is high. However, if they are risk averse, they require high risk premium, making the bank’s financing cost sensitive to default risk.

We thus investigate what affects marginal time depositors’ type. To recall our setting, we consider type $l$ depositors are risk tolerant enough, compared to type $h$ creditors. In particular, denoting the time deposit rate when marginal time depositors are type $t$ by $i_t$, we assume

$$\inf_{0 \leq y < p} (1 - y)i_h(y, (q_0, z)) \geq (1 - p)i_l(p, (q_0, z)),$$

where $p$ is the fraction of type $h$ creditors.

We start with observing $y(q_0, z) \leq (1 - dq_0)/(1 - bq_0)$ from liquidation value constraint. Then, if $p > (1 - dq_0)/(1 - bq_0)$, $f(y(q_0, z)) = h$ because choosing high type is the only option available for the bank. On the other hand, if $p \leq (1 - dq_0)/(1 - bq_0)$, $f(y(q_0, z)) = l$ because choosing low type is feasible for the bank and the bank prefers marginal time depositors to be risk tolerant. On the other hand, if we consider the situation in which there is no risk aversion heterogeneity, $f(y(q_0, z)) = m$, regardless of parameters, where $m$ is common.
type applied for all depositors.

We then claim the following proposition.

**Proposition 2.** Suppose $1 - dq_0 < p \leq (1 - dq_0)/(1 - b_0 q_0)$. Then, marginal time depositors’ type is described in the below table.

<table>
<thead>
<tr>
<th>Capital requirement</th>
<th>Risk aversion heterogeneity</th>
<th>Heterogeneous</th>
<th>Uniform</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b = 0$</td>
<td>$h$</td>
<td>$m$</td>
<td></td>
</tr>
<tr>
<td>$b = b_0$</td>
<td>$l$</td>
<td>$m$</td>
<td></td>
</tr>
</tbody>
</table>

Proof. Omitted.

The above proposition states capital requirement switches the type of marginal time depositors from the risk averse to the risk tolerant only when creditors have diverse attitudes toward risk. A capitalized bank hence experiences relatively mild financing cost when default risk is high in the presence of creditor diversity, enabling it to avoid financial fragility. However, in the absence of creditor diversity, such switching does not occur. In particular, if $m$ represents the moderate level of risk aversion, even a capitalized bank can experience relatively high financing cost when default risk is high. Then, the equilibrium associated with high default risk is likely to exist. In summary, our analysis shows capital requirement is effective conditional on the presence of risk aversion heterogeneity among creditors.

2.3.9 Efficiency

To evaluate the social welfare of each equilibrium, we propose “social return,” $\Pi(s^*)$, as the
measure of efficiency. We specifically define $\Pi(s^*)$ as

$$\Pi(s^*) = q^* \mu - \frac{k}{2} q^{*2} - \Phi(z^*) dq^*.$$  

The first two terms represent the social outcome of risky investment whereas the last term is the expected social loss imposed by the bank’s default, which is the multiple of loss given default, $dq^*$, and the probability of default, $\Phi(z^*)$.

We note this measure does not depend on the capital structure of the bank, given the bank’s risk profile. The bank’s capital structure therefore affects social return only through the bank’s choices of asset and default risks.

We compare the socially optimal asset risk with the equilibrium asset risk in the absence of regulation in order to measure excessive risk taking in a laissez-faire economy. Let $q^0(z^*)$ be the socially optimal level of asset risk given $z^*$, and let $q^e(z^*)$ be the equilibrium asset risk given $z^*$ in the absence of regulation. We denote the extent of excessive risk taking or risk shifting by $\Delta(z^*)$, where $\Delta(z^*) = q^e(z^*) - q^0(z^*)$. Then the following proposition holds:

**Proposition 3.** $\Delta(z^*)$ strictly increases in $z^*$. Therefore, excessive risk taking in the absence of regulation is larger if the equilibrium default risk is larger.

*Proof.* See the appendix A.1.2.

This finding implies the regulatory benefit of restricting asset risk is larger when a bank is closer to default. Therefore, the favorable effect of restricting asset risk is stronger in the high-risk
equilibrium than in the safe equilibrium.

### 2.4 Numerical examples

To assess the relevance of our claims, we provide our model’s numerical examples evaluated at reasonable parameters. We then simulate risk-sensitive capital requirements and liquidity regulations using these examples.

#### 2.4.1 Parameters used for the benchmark case

In the benchmark case, we consider depositors have a uniform risk preference. Specifically, both depositors have a CRRA (constant relative risk aversion) utility function with an RRA (relative risk aversion) of 1.9. We choose this value, considering that commonly accepted measures of the coefficient of RRA lie between 1 and 3 (Gandelman and Hernandez-Murillo, 2015). Table 1 lists the parameters used for our benchmark simulation.

[Insert Table 1]

#### 2.4.2 Financial regulations

Our model is useful for simulating financial regulations recently proposed by the Basel Committee. In 2010, the Basel Committee issued the Basel III rules text. The major changes introduced under Basel III include increasing capital requirements and introducing liquidity requirements. Although capital requirements have been set by the Basel Committee for some time, the new rule raises the minimum capital requirement (as a percentage of risk-weighted assets) by 0.625 percentage points per year (from 8% in 2015, the minimum level specified in Basel II, to 10.5% in 2019). Because our measure of asset risk, $q$, can be considered a risk-weighted asset, we can directly simulate the effect of the risk-sensitive capital requirement by setting $e(q) = bq$, where $b$ is the capital ratio. In the benchmark case, we consider the no-requirement case ($b = 0$).
Moreover, liquidity regulations were introduced for the first time by Basel III, which imposes a minimum net stable funding ratio (NSFR) and minimum liquidity coverage ratio (LCR). Our liquidity constraint captures these requirements by setting $x$ higher than the actual withdrawal. We consider 20% of the demand deposits are withdrawn in the middle of the year. Therefore, in the benchmark case, we set $x = 0.2$. Lastly, we set $\bar{z} = -2$ so that the bank’s default probability does not exceed 2.3%.

2.4.3 Results

2.4.3.1 Benchmark case

In the benchmark case, our analysis suggests the presence of multiple equilibria. Figure 3 presents the benchmark outcome by equilibrium type. In the safe equilibrium, a bank invests 70.8% of its assets in risky ones and almost never defaults. In the high-risk equilibrium, the bank invests 77.4% of its assets in risky ones, and its default probability is 1.2%. The social return is higher in the safe equilibrium (3.0%) than in the high-risk equilibrium (2.6%). These results show the bank’s limited commitment can cause the self-fulfilling prophecy and generate financial instability without involving changes in the bank’s fundamentals. This observation is consistent with the other models, such as Gertler and Kiyotaki (2015) and Egan et al. (2017a).

[Insert Figure 3]

We also find the bank sells 68.0% of the total deposits to the demand depositors in the safe equilibrium, but it sells only 39.3% in the high-risk equilibrium. The issuance of safe demand deposits is crucial for the bank’s risk-sharing function, because it enables risk-averse depositors to invest in the bank without demanding high spreads. This risk-sharing role improves the bank’s solvency, reduces its asset and default risks, and increases social return. Indeed, the bank issues
more demand deposits in the safe equilibrium than in the high-risk equilibrium.

The existence of the high-risk equilibrium indicates the bank cannot costlessly increase demand deposits. Time depositors demand more spreads in accordance with the increase in demand deposits, anticipating the lower liquidation value they can seize at default. In particular, when they anticipate an asset risk above a certain threshold, the bank cannot raise any more demand deposits without violating the liquidation value constraint. In the high-risk equilibrium, the bank is severely restricted in the issuance of demand deposits because time depositors anticipate a high asset risk. Because the bank’s sharing of risks with bank creditors is restricted, the high-risk equilibrium emerges.

2.4.3.2 Eliminating financial fragility

Next, we assess whether the capital requirement and heterogeneity in risk aversion among depositors can mitigate the above concern. When we analyze risk aversion heterogeneity, we consider type $h$ depositors have a CRRA utility function with an RRA of 2.4, whereas type $l$ depositors have a CRRA utility function with an RRA of 0.6. The fraction of type $h$ depositors, $p$, is assumed to be 0.7. Our choice of parameters is set to satisfy the condition that the average RRA in the presence of risk aversion heterogeneity is equal to the benchmark RRA, 1.9. In addition, we consider a capital ratio of 10% when we analyze the effect of the capital requirement ($b = 0.1$).$^{20}$

We start by presenting in figure 4 how the issuable amount of demand deposits is affected by the capital requirement. The figure shows the issuable amount of demand deposits is higher when the capital requirement is present ($b = 0.1$) than when it is absent ($b = 0$). It also shows the issuable amount of demand deposits is decreasing in the anticipated level of the bank’s asset risk.

---

$^{20}$ We also analyze continuous distribution of relative risk aversion in the appendix.
For example, the bank cannot sell 70% of total deposits to demand depositors when depositors anticipate 75% of the bank’s assets are risky at $b = 0$, but selling 70% of total deposits to demand depositors is feasible at $b = 0.1$. Thus, a risk-sensitive capital requirement relaxes the liquidation value constraint, particularly when depositors anticipate a high asset risk.

Still assuming a capital ratio of 10%, we next compute the optimal level of demand deposits and interest expense rate as well as the opportunity cost and value of default for different levels of default probability (and corresponding asset risk) that are rationally anticipated by depositors. Figure 5 presents the results from this analysis. The left panels show the case in which depositors have a uniform risk preference, whereas the right panels present the case in which they have a heterogeneous preference. The top left panel shows demand deposits issued by the bank sharply decrease in the bank’s risk when depositors have a uniform risk preference. The middle left panel shows the interest expense rate rises sharply in accordance with the decrease in the bank’s demand deposits. Consequently, as shown in the bottom left panel, the opportunity cost of default sharply decreases with the bank’s risk and intersects with the value of default. Because the equilibrium emerges at the intersection of the two curves, the high-risk equilibrium occurs when depositors have a uniform risk preference. On the other hand, the top right panel shows that demand deposits issued by the bank do not decrease with the bank’s risk as much when depositors have a heterogeneous risk preference, because marginal time depositors are less risk-averse, demanding lower compensation for losses through default, so the bank can keep issuing demand deposits until the liquidation constraint is binding. The middle right panel shows the interest expense rate shifts downward in accordance with the increase in the bank’s demand deposits. Consequently, as shown in the bottom right panel, the opportunity cost of default shifts upward without intersecting with
the value of default at high default probability. This outcome is also attributable to the presence of the capital requirement, which relaxes the liquidation value constraint when depositors anticipate high default probability (and corresponding high asset risk) and enables the bank to match risky securities to the risk tolerant and safe ones to the risk averse. Thus, the potential for the high-risk equilibrium is eliminated jointly by depositors’ risk aversion heterogeneity and the capital requirement.

To assess the effects of risk aversion heterogeneity and capital requirement on the financial stability of the banking sector, we also simulate the bank’s “worst” equilibrium outcome. Figure 6 reports the simulation outcome. In the presence of risk aversion heterogeneity and the capital requirement, the high-risk equilibrium is eliminated, as described in the previous paragraph.

[Insert Figure 5]

[Insert Figure 6]

Therefore, the bank’s potential risk is lowest, whereas the social return never becomes too low. However, for the other cases in which the high-risk equilibrium occurs, the bank’s potential risk remains relatively high, and the social return could be relatively low.

This analysis reveals capital requirement is necessary, but not sufficient for achieving financial stability. Although it relaxes the liquidation value constraint, depositors need to have a heterogeneous risk preference for a bank to match risky securities to the risk tolerant and safe ones to the risk averse and eliminate the potential for financial fragility.

---

21 In the presence of multiple equilibria, we report the equilibrium outcome with the highest default probability. If no multiple equilibria exist, we report the outcome of the unique equilibrium.
2.4.3.3 Liquidity regulation

Lastly, we look into the effectiveness of the liquidity regulation. The first observation we made is that the liquidity constraint does not bind in the benchmark case. Whenever a bank increases its risk, it simultaneously increases its share of time deposits. This action reduces the demand for liquidity and makes the liquidity constraint hard to bind even when the asset risk is relatively high.

Because the liquidity constraint is hard to bind without regulation, there is room for policy intervention. In particular, we focus on the case with no risk aversion heterogeneity; the capital requirement cannot eliminate the potential for the high-risk equilibrium. To assess the usefulness of the liquidity requirement, we compute the equilibria of a bank funded by depositors with uniform risk preference while setting $x = 2$, thus artificially forcing a bank to invest at least twice the amount of demand deposits in safe assets.

Figure 7 illustrates the safe and high-risk equilibria for different levels of liquidity requirements in the absence of a capital requirement and risk aversion heterogeneity among creditors. For the high-risk equilibrium, when the liquidity requirement tightens, a bank tends to hold fewer risky assets. Social return consequently improves due to the mitigation of excessive risk taking.\(^{22}\) On the other hand, a tight liquidity requirement can force a bank to reduce asset risk excessively in the safe equilibrium. Because a bank rarely defaults, it already chooses an asset risk close to the socially optimal level even in the absence of a liquidity requirement at the safe equilibrium. As a result, a liquidity requirement can reduce social return due to underinvestment. In accordance with Proposition 2, the regulatory benefit of a liquidity requirement is greater in the high-risk

\(^{22}\) Although a liquidity requirement may weaken the risk sharing mechanism (making it difficult to issue demand deposits), this unfavorable effect is limited in the high-risk equilibrium, because the laissez-faire level of demand deposits is already low in this type of equilibrium.
equilibrium than in the safe equilibrium.

[Insert Figure 7]

This analysis reveals imposing a liquidity requirement can be welfare-enhancing in the high-risk equilibrium but can reduce efficiency in the safe equilibrium. Considering the opposing effects of a liquidity requirement on safe and high-risk equilibria, the use of liquidity regulations may be justified as a tradeoff strategy. In particular, when the high-risk equilibrium cannot be eliminated by capital regulations, liquidity regulations may work as a substitute policy.

2.5 Empirical evidence

We seek further evidence for a joint effect of risk-weighted capital requirement and creditor heterogeneity in risk attitudes on the financial stability of a bank. For this purpose, we investigate how a bank’s interest expense rate, which increases in the bank’s risk, is associated with bank risk-weighted capital and creditor heterogeneity in risk attitudes. Our theory predicts a bank’s interest expense rate is lower in the joint presence of them, because the safe equilibrium, in which the bank issues more safe deposits and experiences fewer risky assets and lower default risk than in the high-risk equilibrium, is more likely to occur. We test this hypothesis using the U.S. bank holding company (BHC) data.

2.5.1 Data

2.5.1.1 U.S. BHC data

To capture a BHC’s interest expense rate and risk-weighted capital, we used yearly Reports of Condition and Income (Call Reports) for the period between 2010 and 2015.23 We also used the

---

23This report is called FR Y-9 for BHCs, which contains financial statements data in a consolidated basis.
Summary of Deposits Survey (SOD) conducted yearly by the FDIC.\textsuperscript{24} Using this data set, we measured each BHC’s deposits at the branch level every year. Then, for each BHC-year, we aggregated deposits at the county level. We denote BHC \(i\)’s deposits in county \(c\) as the percentage of BHC \(i\)’s total deposits in year \(t\) by \(D_{i,c,t}\). This variable is defined as

\[
D_{i,c,t} = \frac{\sum_{b \in B_{c,t}^i} \text{Deposits}_{i,b,t}}{\sum_{c \in C_t} \sum_{b \in B_{c,t}^i} \text{Deposits}_{i,b,t}}
\]

where \(b\) is a generic indicator for branch, \(B_{c,t}^i\) is the set of BHC \(i\)’s branches in county \(c\) in year \(t\), and \(C_t\) is the set of U.S. counties for which we do not miss county-level variables in year \(t\). We use this variable as a weight to calculate the weighted averages of county-level variables when generating BHC-level variables.

2.5.1.2 Regulatory and market environment

Since the GFC, an emerging pool of literature has begun to explore the issue of too-big-to-fail (TBTF) and to argue the weakness of safety net regulation such as the moral hazard problem in systemically important banks and government bailouts. To account for the impact of systemic importance on a bank’s risk-taking behavior and interest rate, we control for the dummy variable Global Systemically Important Banks (GSIB). Starting in 2011, the Financial Stability Board (FSB) has published a list for globally systemically important banks on an annual basis. We consider the banks that were included into the list in 2011 to be GSIB.

In addition, market conditions may drive a bank’s risk-taking behavior through both supply and demand sides. To address this concern, we first observe the local macroeconomic environment (unemployment rates and income growth rates) for each county. Then we observe the extent of deposit

\textsuperscript{24}This survey is a requirement for all insured deposit-taking institutions.
competition for each county. In particular, we calculate the county-level Herfindahl-Hirschman Index (HHI) to capture the level of local deposit competition.\textsuperscript{25} At the BHC level, we measure each bank’s overall exposure to market conditions by calculating the weighted averages of county-level variables across counties in which the bank has branches. Specifically, it is calculated as:

\[ AZ_{l,t} = \sum_{c \in C_t} D_{l,c,t} Z_{c,t}, \]

where \( Z_{c,t} \) is the county-level variable for the market environment (unemployment rates, income growth rates, and HHI).

2.5.1.3 Risk preference index

To measure creditor heterogeneity in risk attitudes, we collected county-level demographic variables from the County Health Rankings & Roadmaps program. The program is conducted by the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute. The data span from 2010 to 2016. Among the available variables, we chose the rate of the uninsured, the adult smoking rate, the teen birth rate, and the chlamydia infection rate as proxies for risk preference. Each variable is considered a relevant proxy for risk preference, given that the previous research supports the association of these variables with risk appetite. We explain the relevance of each variable in the following paragraph.

- **Uninsurance**: Insurance is a financial product used to hedge risks for individuals. Barseghyan et al. (2013) infer risk preference from insurance choices. Moreover, Barsky et al. (1997) find correlation between being uninsured and the indicators for financial risk taking. We

\textsuperscript{25} For example, if there are two banks (bank A and bank B) in the county and bank A’s deposit is 50 whereas bank B’s deposit is 50, the HHI for the county is \( \left( \frac{50}{50+50} \right)^2 + \left( \frac{50}{50+50} \right)^2 = 0.5 \).
therefore consider the uninsured population a proxy for risk preference.

- **Adult smoking**: Numerous health studies have established the fact that smoking is the leading risk factor for various diseases and for death from cancer (e.g., Lim, S.S., et al. (2012)). Therefore, a smoker who is aware of this fact can be considered less risk averse. However, distinguishing misinformation from risk taking is difficult. For instance, young people may smoke due to misinformed risk (Leventhal et al., 1987). To address this concern, we chose the adult smoking rate as our proxy for risk preference in health choice.

- **Teen birth**: Schmidt (2008) suggests females with greater tolerance for risk experience tend to experience earlier births and less effective contraception. Therefore, we chose teen birth as our proxy for risk preference.

- **Chlamydia infection**: Baeten et al. (2001) find consistent condom use can significantly reduce the risk of sexually transmitted infections, including chlamydia. On the other hand, the use of condoms is also considered a key indicator of sexual risk taking (Tapert et al., 2001). As a result, we chose the chlamydia infection rate as another proxy for risk preference in sexual behavior.

Although different factors might affect health-related and financial risk taking, Barsky et al. (1997) find their unique measure of risk tolerance predicts a wide range of risky behaviors, including smoking, drinking, failing to have insurance, and holding stocks rather than Treasury bills. Moreover, Calvet and Sodini (2014) reveal the proportion of the liquid financial portfolio invested in risky assets is positively linked to health risk-taking factors such as alcohol consumption.

Because each variable may capture a behavioral factor that is irrelevant to risk preference, we
performed a principle component analysis (PCA) to reduce noise.\textsuperscript{26} The first component has an eigenvalue of 2.02 and is the only component that has an eigenvalue higher than 1. It alone explains 51\% of the variations in the data. The following equation describes the structure of the risk preference index for county $c$ in year $t$:

$$ RPI_{c,t} = 0.4780 Uninsured_{c,t} + 0.4140 Smoking_{c,t} + 0.6345 TeenBirth_{c,t} + 0.4444 Chlamydia_{c,t}. $$

The factor loading of each proxy is positive, which captures the positive relationship between our proxies and underlying risk preference. We find the correlation between the index that we construct from PCA and the probability of being uninsured, the proxy most directly related to financial risk taking, is 0.6799. The strong correlation between them suggests the index is a relevant measure of financial risk preference.

After constructing the county-year level risk preference index, $RPI_{c,t}$, we calculated the average and weighted standard deviation of each county’s risk preference index per bank-year, considering the bank’s deposits located in each county, $D_{i,c,t}$, as the weight. Specifically, the average risk preference index, $ARPI_{i,t}$, is calculated as

$$ ARPI_{i,t} = \sum_{c \in C_t} D_{i,c,t} \ast RPI_{c,t}. $$

Then, we generated the risk preference heterogeneity, $RPH_{i,t}$, by the following:

$$ RPH_{i,t} = \sqrt{\sum_{c \in C_t} (D_{i,c,t} \ast (RPI_{c,t} - ARPI_{i,t})^2)}. $$

The risk preference heterogeneity, $RPH_{i,t}$, captures the bank creditors’ risk preference.

\textsuperscript{26} We used standardized proxies to perform PCA.
heterogeneity. Table 2 reports the summary statistics of the merged data. In the merged data, we have 1,058 banks and 4,790 observations.

Figure 8 shows the median of risk preference heterogeneity for community banks and large banks in our samples. In line with our expectations, we find community banks have less diverse creditors than large banks.

2.5.2 Empirical analysis

To estimate the effect of risk-weighted capital and creditor diversity in risk attitudes on a bank’s interest expense rate, we estimate the ordinary least squares (OLS) regression by the following equation:

\[ IR_{i,t} = \alpha + \beta RPH_{i,t} \times RWE_{i,t} + \theta RPH_{i,t} + \delta RWE_{i,t} + \Gamma * X_{i,t} + \epsilon_{i,t} \] (1)

where \( IR_{i,t} \) represents bank \( i \)'s interest expense rate paid to creditors in year \( t \), \( RPH_{i,t} \) is the bank’s exposure to creditor diversity in risk attitudes, and \( RWE_{i,t} \) characterizes the one-year lagged risk-weighted equity ratio of the bank. Specifically, we measure \( IR_{i,t} \) by dividing interest expenses over total liabilities and \( RWE_{i,t} \) by taking the ratio of total equity to risk weighted assets in the previous year. \( X_{i,t} \) is the set of control variables, including \( AZ_{i,t} \) and \( ARPI_{i,t} \).\(^{27}\)

To detrend variables, we also include year dummies in \( X_{i,t} \). In this specification, the explanatory variable of interest is the interaction term \( RPH_{i,t} \times \)

\(^{27}\) We do not include endogenous variables, such as profitability, because our dependent variable, interest rate, directly affects a bank’s profits.
The coefficient on this term, $\beta$, captures the joint effect of risk-weighted capital and creditor diversity in risk attitudes on a bank’s interest expense rate. Note we include bank size and age in the set of control variables, which can potentially explain some of the variations in interest expense rates.

Column (1) in table 3 reports the outcome of this regression. We find $\beta$ is estimated to be negative and statistically significant at the 5% level. This result suggests capitalized banks exposed to higher levels of creditor diversity experience, on average, lower interest expense rates. In other words, a bank’s risk tends to be lower in the joint presence of capital adequacy and creditor diversity in risk attitudes. On the other hand, our estimates for $\theta$ and $\delta$ are statistically insignificant. This result implies neither risk-weighted capital nor creditor diversity in risk attitudes is likely to reduce a bank’s risk by itself. Overall, our finding is consistent with our simulation outcome; that is, the high-risk equilibrium vanishes only in the joint presence of risk-weighted capital and risk aversion heterogeneity among creditors.

We note the coefficients reported in column (1) are estimated using both time-series and cross-sectional variations in our data. Because we detrend variables by including year dummies, time-series variations are somewhat suppressed though not perfectly eliminated. Given that our theoretical predictions are based on differences in risk-weighted capital ratios and exposure to creditor diversity across banks, a more appropriate test of our predictions would involve estimating $\beta$ by relying entirely on cross-sectional variations in our data.

To perform a more appropriate test, we re-estimate $\beta$ using the between-group estimator. Specifically, we estimate the following model:
\[
\overline{IR}_i = \alpha + \beta RPH_i \times \overline{RWE}_i + \theta RPH_i + \delta \overline{RWE}_i + \Gamma \times \overline{X}_t + \overline{\epsilon}_t, \tag{2}
\]

where each variable is averaged over time at the bank level.

We report our estimates based on this alternative specification in column (2). In this case, the coefficient on the interaction term is negative and statistically significant at the 1% level, whose magnitude is similar to the result in column (1). This result further supports the consistency of our simulation outcome with our empirical evidence.

Lastly, we perform multiple robustness checks in the appendix. Overall, we obtain estimation results similar to our benchmark estimates.

2.6 Discussion

Our finding that risk aversion heterogeneity across depositors and moderate capital requirements jointly eliminate the potential for a sunspot crisis has a direct policy implication concerning the appropriate level of capital ratio, which has been widely debated among both academics and practitioners.\(^{28}\) We contribute to this debate by arguing that the appropriate capital ratio level depends on the diversity of creditors’ risk attitudes. We find a capital ratio of 10% is sufficient for eliminating financial fragility in the presence of risk aversion heterogeneity among creditors, but not in the absence of such heterogeneity. Thus, this result shows the efficiency of capital regulation is contingent on the heterogeneity of risk aversion among depositors.

Our finding is consistent with the proposed regulation that imposes heavier capital requirements on large banks as long as large banks have more diverse depositors than community banks. Our analysis, however, also reveals banks that have less diverse creditors cannot avoid financial crisis.

\(^{28}\) For example, Begenau (2016) argues the optimal capital ratio is around 15%, whereas Van den Heuvel (2008) suggests a capital ratio of 10% imposes a welfare cost of between 0.1 and 1.0% of consumption.
Because liquidity requirements mitigate excessive risk taking during the financial crisis, our analysis suggests regulators should retain the option of imposing liquidity requirements on community banks. Overall, this paper suggests deregulating community banks may not necessarily be optimal.

Although our model endogenizes a variety of a bank’s strategies, including investment and default decisions, liability structure choice, and deposit pricing under the condition of limited commitment, it leaves several issues open. For example, we have not explicitly modeled interbank risk sharing agreements in our main analysis. In addition, we have not modeled state evolution over time. Because our model focuses on stationary equilibria, it does not capture time-series variations within a bank, and best fits to explain cross-sectional variations across local monopolistic banks.\textsuperscript{29} Another issue is that our model assumes depositors’ liquidity preference shocks are independent of realized asset returns. If they were correlated, a bank would not be able to fully predict the amount of deposit withdrawal ex ante. Then the bank could default from forced liquidation due to the large withdrawal of demand deposits before the maturity of asset. The bank’s investment choice would directly affect its default probability in this case. We recommend addressing these issues in future research.

\textsuperscript{29} For example, our model does not predict how a bank’s liability size and structure evolves over time.
2.7 References


2.8 Appendix

2.8.1 A.1 Proofs

A.1.1 Proof for Proposition 1

The closed form of $V(y, s, s^d)$ is derived by

\[
V(y, s, s^d) = \frac{1 - \Phi(z)}{1 + r} \left( q(\mu + \sigma \lambda(z)) - c(y, s, s^d) - \frac{k}{2} q^2 + V(y, s, s^d) \right) - \frac{(\Phi(z) + \gamma) e(q)}{1 + r}
\]

\[
\frac{r + \Phi(z)}{1 + r} V(y, s, s^d) = \frac{1 - \Phi(z)}{1 + r} \left( q(\mu + \sigma \lambda(z)) - c(y, s, s^d) - \frac{k}{2} q^2 \right) - \frac{(\Phi(z) + \gamma) e(q)}{1 + r}
\]

\[
V(y, s, s^d) = \frac{1 + r}{r + \Phi(z)} \left( q(\mu + \sigma \lambda(z)) - c(y, s, s^d) - \frac{k}{2} q^2 \right) - \frac{(\Phi(z) + \gamma) e(q)}{r + \Phi(z)}
\]

First, I consider the case in which the liquidity constraint does not bind. Because we focus on the interior solution $s^*$, the solution has to satisfy the first order conditions with respect to asset risk $q$ and tail risk $z$, respectively. Also, rational expectation requires $s^d = s^*$. The partial derivative of the value function with respect to $q$ at the optimized $y, y^*$, is

\[
\frac{\partial V(y^*, s^*, s^*)}{\partial q} \propto \mu + \sigma \lambda(z^*) - kq^* + e'(q^*) \left( (1 - y^*)i(y^*, s^*) - \frac{\Phi(z^*) + \gamma}{1 - \Phi(z^*)} \right).
\]

Since $s^*$ satisfies $\frac{\partial V(y^*, s^*, s^*)}{\partial q} = 0$, $s^*$ also satisfies

\[
\mu + \sigma \lambda(z^*) - kq^* + e'(q^*) \left( (1 - y^*)i(y^*, s^*) - \frac{\Phi(z^*) + \gamma}{1 - \Phi(z^*)} \right) = 0.
\]

Thus, $s^*$ satisfies:
\[
\mu + \sigma \lambda(z^*) + c'(q^*) \left( (1 - y^*) i(y^*, s^*) - \frac{\Phi(z^*) + \gamma}{1 - \Phi(z^*)} \right) = kq^*
\]
\[
\frac{1 - \Phi(z^*)}{r + \Phi(z^*)} \left( \mu + \sigma \lambda(z^*) + c'(q^*) \left( (1 - y^*) i(y^*, s^*) - \frac{\Phi(z^*) + \gamma}{1 - \Phi(z^*)} \right) \right) = \frac{1 - \Phi(z^*)}{r + \Phi(z^*)} kq^*.
\]

In addition, I can characterize the partial derivative of the value function with respect to \(z\) as follows:

\[
\frac{\partial V(y^*, s^*, s^*)}{\partial z} = -\frac{r \phi(z^*) e(q^*)}{(r + \Phi(z^*))^2} + \frac{\gamma \phi(z^*) e(q^*)}{(r + \Phi(z^*))^2} - \phi(z^*)(1 + r) \pi(y^*, s^*, s^*) + \frac{1 - \Phi(z^*)}{r + \Phi(z^*)} q^* \sigma \lambda(z^*)(\lambda(z^*) - z^*)
\]
\[
- \frac{r \phi(z^*) e(q^*)}{(r + \Phi(z^*))^2} + \frac{\gamma \phi(z^*) e(q^*)}{(r + \Phi(z^*))^2} - \frac{\phi(z^*)(1 + r)}{r + \Phi(z^*)} \pi(y^*, s^*, s^*) + \frac{1 - \Phi(z^*)}{r + \Phi(z^*)} \frac{\phi(z^*)}{1 - \Phi(z^*)} q^* \sigma (\lambda(z^*) - z^*)
\]
\[
- \frac{r \phi(z^*) e(q^*)}{(r + \Phi(z^*))^2} + \frac{\gamma \phi(z^*) e(q^*)}{(r + \Phi(z^*))^2} - \frac{1}{1 + r} q^* \sigma (\lambda(z^*) - z^*) - r - \gamma e(q^*) \frac{1}{1 + r + \Phi(z^*)}.
\]

where \(\pi(y, s, s^d) = q(\mu + \sigma \lambda(z)) - c(y, s, s^d) - \frac{k q^2}{2}\). Because \(s^*\) satisfies \(\frac{\partial V(y^*, s^*, s^*)}{\partial z} = 0\), \(s^*\) also satisfies \(-\frac{\pi(y^*, s^*, s^*)}{r + \Phi(z^*)} + \frac{1}{1 + r} q^* \sigma (\lambda(z^*) - z^*) - r - \gamma e(q^*) \frac{1 + r}{1 + r + \Phi(z^*)} = 0\). Thus, \(s^*\) satisfies:

\[
- \frac{\pi(y^*, s^*, s^*)}{r + \Phi(z^*)} + \frac{1}{1 + r} q^* \sigma (\lambda(z^*) - z^*) - r - \gamma e(q^*) \frac{1 + r}{1 + r + \Phi(z^*)} = 0
\]
\[
(\gamma + \Phi(z^*)) e(q^*) \frac{1 - \Phi(z^*)}{r + \Phi(z^*)} \pi(y^*, s^*, s^*) + \frac{1 - \Phi(z^*)}{r + \Phi(z^*)} q^* \sigma (\lambda(z^*) - z^*) - \frac{1}{1 + r} (1 + \gamma) e(q^*) = 0
\]
\[
q^* (1 - \Phi(z^*)) (\lambda(z^*) - z^*) - \frac{1}{1 + r} (1 + \gamma) e(q^*) = V(y^*, s^*, s^*).
\]
Next, we consider the case in which the liquidity constraint binds. Because $V(y, s, s^d)$ is not differentiable with respect to $y$, we cannot use the Lagrange multipliers method. Instead, we use the substitution method. We thus have

$$(y^*, z^*) \in \arg \max_{(y, z) \in [0,1] \times \mathbb{R}} V(y, (Q(y), z), s^*) \text{ s.t. } 1 - dq^* \geq (1 - e(q^*))y.$$ 

Our goal is to further characterize the optimality condition. Because $V$ is differentiable in the $z$-direction for fixed $y$ anywhere, the partial derivative of $V$ with respect to $z$ has to be zero at $z^*$, which is located in the interior of an open interval due to the equilibrium definition. Therefore, $\frac{\partial V(y^*, s^*, z^*)}{\partial z} = 0$ has to be satisfied. Then $y^*$ satisfies

$$y^* \in \arg \max_{y \in [0,1]} V(y, (Q(y), z^*), s^*) \text{ s.t. } 1 - dq^* \geq (1 - e(q^*))y.$$ 

A.1.2 Proof for Proposition 3

Consider no regulation so that $e(q) = x = 0$. From Proposition 1,

$$q^e(z^*) = \frac{\mu + \sigma \lambda(z^*)}{k}$$

In addition, $\frac{\partial n(q^0(z^*), z^*)}{\partial q^*} = 0$ implies

$$q^0(z^*) = \frac{\mu - \Phi(z^*)d}{k}$$

Then, the excessive asset risk can be characterized by

$$\Delta(z^*) = \frac{\mu + \sigma \lambda(z^*)}{k} - \frac{\mu - \Phi(z^*)d}{k} = \frac{\sigma \lambda(z^*) + \Phi(z^*)d}{k}$$

Therefore, we can show
\[
\frac{\partial \Delta(z^*)}{\partial z^*} = \frac{1}{k} \frac{\partial (\sigma \lambda(z^*) + \Phi(z^*)d)}{\partial z^*} > 0
\]

because the hazard function of the normal distribution is a strictly increasing function.

A.1.3 Derivation of equilibrium default risk in section 2.3.9

From the proof of Proposition 1, we have:

\[
\frac{\partial V(y^*, s^*, s^*)}{\partial z} \propto -\frac{\pi(y^*, s^*, s^*)}{r + \Phi(z^*)} + \frac{1}{1 + r} q^* \sigma(\lambda(z^*) - z^*) - \frac{r - \gamma}{1 + r} \frac{e(q^*)}{\Phi(z^*)}
\]

\[
\propto -\pi(y^*, s^*, s^*) + \frac{r + \Phi(z^*)}{1 + r} q^* \sigma(\lambda(z^*) - z^*) \quad \text{due to } \gamma = r.
\]

\[
\frac{\partial V(y^*, s^*, s^*)}{\partial z} = 0 \quad \text{is equivalent to} \quad \frac{r + \Phi(z^*)}{1 + r} q^* \sigma(\lambda(z^*) - z^*) = \pi(y^*, s^*, s^*). \quad \text{Replacing } s^* \text{ by } (q_0, z^*)
\]

and \(y^*\) by \(y(q_0, z^*)\), we obtain the condition for equilibrium default risk in section 3.8.

A.1.4 Derivation of social return

\[
\Pi(s^*) = \left(1 - \Phi(z^*)\right) \left( q^*(\mu + \lambda(z^*)) - c(y^*, s^*, s^*) - k q^* \right) - (\gamma + \Phi(z^*))e(q^*)
\]

\[
+ \left(1 - e(q^*)\right) \left( \left(1 - \Phi(z^*)\right)(1 + i(y^*, s^*)) + \Phi(z^*) \frac{1 - q^* + q^*(1 - d)}{1 - e(q^*)} - 1 \right)
\]

\[
- \Phi(z^*) \left( q^* \left( \frac{\phi(z^*)}{\Phi(z^*)} - \mu \right) + k q^* \right) + \gamma e(q^*)
\]

\[
= q^* \mu - \frac{k}{2} q^* - \Phi(z^*) dq^*.
\]

2.8.2 A.2 Continuous distribution of relative risk aversion

In this section, we assume depositors’ relative risk aversion (RRA) \(\eta\) follows a gamma distribution \(G(\alpha, \beta)\), where \(\alpha\) is the shape parameter and \(\beta\) is the scale parameter. The
cumulative distribution function (CDF) of the distribution is \( F(\eta) = \frac{1}{\Gamma(\alpha)} \frac{\gamma(\alpha, \frac{\eta}{\beta})}{\gamma(\alpha)} \). As in the discrete case, if a bank sets the same time deposit rate to every depositor, less risk-averse depositors would self-select into time deposits and more risk-averse depositors would self-select into demand deposits. In particular, when the bank issues \( y \) fraction of total deposits as demand deposits, any depositor with RRA \( \eta > \eta^*(y) \) would choose demand deposits, and those with RRA \( \eta \leq \eta^*(y) \) would choose time deposits. The cut-off risk aversion \( \eta^*(y) \) satisfies the following relationship:

\[
\eta^*(y) = F^{-1}(1 - y).
\]

With regard to the pricing of time deposits, the time deposit rate \( i(y, s^d) \) depends on the RRA of the marginal depositor \( \eta^*(y) \) and satisfies the following relationship:

\[
i(y, s^d) = \min \left\{ \left( 1 - \Phi(z^d) \right) U_{\eta^*(y)}(1 + i) + \Phi(z^d) U_{\eta^*(y)} \left( \frac{1 - dq^d - (1 - e(q^d))y}{(1 - e(q^d))(1 - y)} \right) \right\},
\]

where \( U_{\eta^*(y)}(\cdot) \) is the utility function with RRA of \( \eta^*(y) \). The time deposit rate \( i(y, s^d) \) is determined when the equality holds.

In general, depositors who are more risk-averse than the marginal depositor would demand a higher risk premium from a risky product (i.e., time deposits). Because the time deposit rate \( i(y, s^d) \) is the minimum rate such that the marginal depositor weakly prefers time deposits to riskless bond, any depositor with higher \( \eta \) would find the rate generates a lower expected utility than the utility from riskless bond. Therefore, such a depositor would find time deposits unattractive and choose demand deposits that are as attractive as riskless bond to them. Vice versa, depositors who are less risk-averse than the marginal depositor would always find time
deposits at least as attractive as riskless bond and demand deposits that are as attractive as riskless bond to them. Thus, depositors with RRA of $\eta > \eta^*(y)$ would choose demand deposits, whereas depositors with RRA of $\eta \leq \eta^*(y)$ would choose time deposits.

For numerical analysis, we compare two scenarios: “Low diversity” and “High diversity” in correspondence with “Uniform” and “Heterogeneous” scenarios in the previous numerical example under which the distribution of RRA is discrete.\(^1\) Both scenarios of the current analysis assume the mean RRA of 1.9, which is identical to the scenarios in the previous numerical example. In the low-diversity scenario, the distribution of RRA has a variance of 0.01. In the high-diversity scenario, the distribution of RRA has a variance of 10. Except for the distribution of RRA, we keep using the same set of parameters that we use for the previous numerical example.

Figures A.1 and A.2 present the results that correspond to figures 5 and 6 in the previous numerical example. Figure A.1 suggests the high-risk equilibrium vanishes in the presence of moderate capital requirement only in the high-diversity scenario. Correspondingly, Figure A.2 shows the social return becomes substantially large in the presence of moderate capital requirement only in the high-diversity scenario. Figure A.1 also reveals the amount of demand deposits is constantly high and smooth in the high-diversity scenario, whereas it is discontinuously shifted up in the corresponding scenario of the previous numerical example. Although the high-risk equilibrium is eliminated due to relatively high demand deposits in the high-diversity scenario and the corresponding scenario in the previous numerical example, the distributional form of RRA alters the schedule for the opportunity cost of default through this difference. Overall, the result from this analysis is qualitatively similar to the corresponding

\(^1\) We note the definition and solution of equilibrium as well as the measure of efficiency is not altered by the distributional form of RRA. We hence keep using Definition 1, the measure of social return, and Propositions 1 and 2.
result from the previous numerical example despite the difference in detail.

[Insert Figure A.1]

[Insert Figure A.2]

2.8.3 A.3 Robustness

In this section, we performed multiple robustness checks for our empirical analysis.

One concern is that our proxies for risk preference may capture county characteristics that are not directly related to risk preference. In this case, our measure of risk preference heterogeneity may not be relevant for our study. For example, a depositor’s educational attainment, which is likely to capture the availability of information about bank risk for a depositor, can be correlated with the risk preference of a depositor. Because a bank can improve its solvency by matching the riskiness of its securities to its depositors’ insensitivity to bank risk, the heterogeneity in educational attainment, instead of risk preference heterogeneity, may cause our results. To address this potential issue, we first regressed each of our proxies on a comprehensive set of county demographics, which are listed in table A.1, and then used regression residuals as the components that generate risk preference indices. This process guarantees risk preference indices are orthogonal to any other county characteristic that could potentially co-move with risk preference.

[Insert Table A.1]

After this process, we re-ran the benchmark regression model based on these residual risk preference indices. We report regression results in table A.2, in which column numbers correspond to equation numbers. In both columns, the coefficients on the interaction term, $\beta$, are still negative and as statistically significant as those reported in table 3. Moreover, the coefficients’ magnitudes are similar to the corresponding estimates in table 3 for both columns. This result suggests our benchmark estimates stay robust to the control of county-level
demographics that may co-move with risk preference index.

Another concern is that the estimated joint effect of risk-weighted bank capital and creditor heterogeneity in risk attitudes may reflect the heterogeneous effect of bank capital on bank risk.

[Insert Table A.2]

[Insert Table A.3]

For example, if bank capital is negatively associated with bank risk for a larger bank, but not for a smaller bank, the estimated $\beta$ can be negative, even if it is not driven by creditor heterogeneity in risk attitudes. To tease out this possibility, we re-ran the benchmark regression model while controlling for the interaction of bank size and risk-weighted equity ratio. We report regression results in table A.3. We find the estimate of $\beta$ is similar to the benchmark estimate.

Overall, we obtain the regression results similar to our benchmark estimates.
2.9 Tables and Figures

Figure 1: bank Balance Sheet
Figure 2: Bank Life Cycle

<table>
<thead>
<tr>
<th>...</th>
<th>Year -2</th>
<th>Year -1</th>
<th>Year 1</th>
<th>Year 2</th>
<th>...</th>
<th>Year X-1</th>
<th>Year X</th>
<th>Year X+1</th>
<th>Year X+2</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>Continue</td>
<td>Default</td>
<td>Start</td>
<td>Continue</td>
<td>...</td>
<td>Continue</td>
<td>Default</td>
<td>Start</td>
<td>Continue</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>Step 1</td>
<td>Step 1</td>
<td>Step 1</td>
<td>Step 1</td>
<td>...</td>
<td>Step 1</td>
<td>Step 1</td>
<td>Step 1</td>
<td>Step 1</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>Step 2</td>
<td>Step 2</td>
<td>Step 2</td>
<td>Step 2</td>
<td>...</td>
<td>Step 2</td>
<td>Step 2</td>
<td>Step 2</td>
<td>Step 2</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>Step 3</td>
<td>Step 3</td>
<td>Step 3</td>
<td>Step 3</td>
<td>...</td>
<td>Step 3</td>
<td>Step 3</td>
<td>Step 3</td>
<td>Step 3</td>
<td>...</td>
</tr>
</tbody>
</table>
Table 1: Parameters for Simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Notation</th>
<th>Value</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk free rate</td>
<td>$r$</td>
<td>0.020</td>
<td>U.S. 1-year TB rate as of March 2018</td>
</tr>
<tr>
<td>Cost of capital</td>
<td>$\gamma$</td>
<td>0.030</td>
<td>U.S. long-term TB rate as of March 2018</td>
</tr>
<tr>
<td>Mean risky asset ret.</td>
<td>$\mu$</td>
<td>0.085</td>
<td>Matched to mean ROA in Egan et al. (2017a) at the safe equilibrium</td>
</tr>
<tr>
<td>Risky asset ret. vol.</td>
<td>$\sigma$</td>
<td>0.25</td>
<td>Matched to standard deviation of ROA in Egan et al. (2017a) at the</td>
</tr>
<tr>
<td>LGD for risky assets</td>
<td>$d$</td>
<td>0.45</td>
<td>Recover rate of 0.55 for risky assets (See Schuermann (2004) for the</td>
</tr>
<tr>
<td>Operating cost coeff.</td>
<td>$k$</td>
<td>0.12</td>
<td>Matched to 0.7 (0.3) for the fraction of risky (safe) assets at the</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>safe equilibrium (Liquid assets/total assets ranged from 23 % to 31 %</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>in the U.S. between 2003 and 2013 (Buehler et al., 2013).</td>
</tr>
</tbody>
</table>
Figure 3: Benchmark Outcome

Note: The figure presents the risk and social return by equilibrium type for the benchmark case.
Figure 4: Issuable Demand Deposits
Figure 5: Bank’s Strategies and Equilibria

Note: The figure presents the optimal level of demand deposits and interest expense rate as well as the opportunity cost and value of default for different levels of default probability (and corresponding asset risks) depositors rationally anticipate. The opportunity cost and value of default are converted into corresponding flow items. We consider a 10% capital ratio \( (b = 0.1) \). The white rectangles represent equilibria in the bottom panels.
Figure 6: Bank’s Financial Stability

Note: The figure presents the equilibrium risk and social return at the “worst” equilibrium. In the presence of multiple equilibria, we choose the one with the largest default probability, highest asset risk, and lowest social return.
Figure 7: Effect of Liquidity Requirement

Note: The figure presents the risk and social return for each equilibrium in the absence of risk aversion heterogeneity. We set $b = 0$. 
Table 2: Summary Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Mean</th>
<th>Sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest expense rate (%)</td>
<td>4,790</td>
<td>0.814</td>
<td>0.516</td>
</tr>
<tr>
<td>Risk preference heterogeneity</td>
<td>4,790</td>
<td>0.607</td>
<td>0.414</td>
</tr>
<tr>
<td>Lagged risk weighted equity ratio</td>
<td>4,790</td>
<td>0.143</td>
<td>0.070</td>
</tr>
<tr>
<td>Average risk preference</td>
<td>4,790</td>
<td>-0.261</td>
<td>1.149</td>
</tr>
<tr>
<td>Lagged log total assets (log thousands of dollars)</td>
<td>4,790</td>
<td>14.249</td>
<td>1.307</td>
</tr>
<tr>
<td>Bank age (years)</td>
<td>4,790</td>
<td>22.954</td>
<td>13.515</td>
</tr>
<tr>
<td>Average HHI</td>
<td>4,790</td>
<td>0.213</td>
<td>0.092</td>
</tr>
<tr>
<td>Average unemployment rate (%)</td>
<td>4,790</td>
<td>7.361</td>
<td>2.188</td>
</tr>
<tr>
<td>Average income growth (%)</td>
<td>4,790</td>
<td>1.523</td>
<td>2.860</td>
</tr>
<tr>
<td>Global systemically important banks</td>
<td>4,790</td>
<td>0.010</td>
<td>0.099</td>
</tr>
</tbody>
</table>

Note: The sample period of the merged data ranges from 2010 to 2015.
Figure 8: Creditor Diversity

Note: The figure presents the median of risk preference heterogeneity for each of community and large banks. We consider observations with bank assets smaller than 10 billion dollars as community banks and the remaining observations as large banks.
Table 3: Regression Results

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk preference heterogeneity × Lagged risk weighted equity ratio</td>
<td>(-0.969^{**})</td>
<td>(-0.948^{***})</td>
</tr>
<tr>
<td>Risk preference heterogeneity</td>
<td>(0.0657)</td>
<td>(0.0784)</td>
</tr>
<tr>
<td>Lagged risk weighted equity ratio</td>
<td>(0.111)</td>
<td>(0.00709)</td>
</tr>
<tr>
<td>Average risk preference</td>
<td>(-0.0187^{*})</td>
<td>(-0.0171)</td>
</tr>
<tr>
<td>Lagged log total assets</td>
<td>(-0.659^{***})</td>
<td>(-0.563^{***})</td>
</tr>
<tr>
<td>Lagged log total assets squared</td>
<td>(0.0217^{***})</td>
<td>(0.0183^{***})</td>
</tr>
<tr>
<td>Bank age</td>
<td>(-0.00377)</td>
<td>(-0.00480^{***})</td>
</tr>
<tr>
<td>Average HHI</td>
<td>(0.154)</td>
<td>(-0.00255)</td>
</tr>
<tr>
<td>Average unemployment rate</td>
<td>(-0.00561)</td>
<td>(-0.00676)</td>
</tr>
<tr>
<td>Average income growth</td>
<td>(-0.00202)</td>
<td>(-0.0191^{**})</td>
</tr>
<tr>
<td>Global systemically important banks</td>
<td>(-0.741^{**})</td>
<td>(-0.543^{***})</td>
</tr>
<tr>
<td>Year dummies</td>
<td>(X)</td>
<td>(X)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,790</td>
<td>4,790</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.420</td>
<td>0.320</td>
</tr>
</tbody>
</table>

Note: In column (2), we report between-\(R^2\). Standard errors are in parentheses and clustered at bank level. * p < 0.10, ** p < 0.05, *** p < 0.01.
Figure A.1: Bank’s Strategies and Equilibria (Continuous RRA Distribution)

Note: The figure presents the optimal level of demand deposits and interest expense rate as well as the opportunity cost and value of default for different levels of default probability (and corresponding asset risks) that depositors rationally anticipate. The opportunity cost and value of default are converted into corresponding flow items. We consider a 10% capital ratio ($b = 0.1$). The white rectangles represent equilibria in the bottom panels.
Figure A.2: Bank’s Financial Stability (Continuous RRA Distribution)

Note: The figure presents the equilibrium risk and social return at the “worst” equilibrium. In the presence of multiple equilibria, we choose the one with the largest default probability, highest asset risk, and lowest social return.
Table A.1: County Demographics

<table>
<thead>
<tr>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of population ages below 18</td>
</tr>
<tr>
<td>Percentage of population ages 65 and over</td>
</tr>
<tr>
<td>Percentage of African Americans</td>
</tr>
<tr>
<td>Percentage of American Indians/ Alaskan Natives</td>
</tr>
<tr>
<td>Percentage of Asians</td>
</tr>
<tr>
<td>Percentage of Native Hawaiians/ Other Pacific Islanders</td>
</tr>
<tr>
<td>Percentage of Hispanics</td>
</tr>
<tr>
<td>Percentage of population not proficient in English</td>
</tr>
<tr>
<td>Percentage of females</td>
</tr>
<tr>
<td>Percentage of rural population</td>
</tr>
<tr>
<td>Median household income</td>
</tr>
<tr>
<td>Percentage of children eligible for free lunch</td>
</tr>
<tr>
<td>Percentage of population ages 16 and older unemployed but seeking work</td>
</tr>
<tr>
<td>Percentage of children under age 18 in poverty</td>
</tr>
<tr>
<td>Averaged freshman graduation rate</td>
</tr>
<tr>
<td>Percentage of single-parent households</td>
</tr>
</tbody>
</table>
Table A.2: Regression Results (Residual Risk Preference Index)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual risk preference heterogeneity × Lagged risk weighted equity ratio</td>
<td>-0.793**</td>
<td>-1.079**</td>
</tr>
<tr>
<td></td>
<td>(0.400)</td>
<td>(0.428)</td>
</tr>
<tr>
<td>Residual risk preference heterogeneity</td>
<td>0.0545</td>
<td>0.0903</td>
</tr>
<tr>
<td></td>
<td>(0.0742)</td>
<td>(0.0767)</td>
</tr>
<tr>
<td>Lagged risk weighted equity ratio</td>
<td>0.0113</td>
<td>-0.0329</td>
</tr>
<tr>
<td></td>
<td>(0.340)</td>
<td>(0.211)</td>
</tr>
<tr>
<td>Average residual risk preference</td>
<td>-0.0413***</td>
<td>-0.0380***</td>
</tr>
<tr>
<td></td>
<td>(0.0143)</td>
<td>(0.0132)</td>
</tr>
<tr>
<td>Lagged log total assets</td>
<td>-0.645***</td>
<td>-0.484***</td>
</tr>
<tr>
<td></td>
<td>(0.190)</td>
<td>(0.151)</td>
</tr>
<tr>
<td>Lagged log total assets squared</td>
<td>0.0214***</td>
<td>0.0161***</td>
</tr>
<tr>
<td></td>
<td>(0.00656)</td>
<td>(0.00490)</td>
</tr>
<tr>
<td>Bank age</td>
<td>-0.00363*</td>
<td>-0.00429***</td>
</tr>
<tr>
<td></td>
<td>(0.00220)</td>
<td>(0.000900)</td>
</tr>
<tr>
<td>Average HHI</td>
<td>0.132</td>
<td>0.0238</td>
</tr>
<tr>
<td></td>
<td>(0.159)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Average unemployment rate</td>
<td>-0.0100</td>
<td>-0.0127*</td>
</tr>
<tr>
<td></td>
<td>(0.00674)</td>
<td>(0.00693)</td>
</tr>
<tr>
<td>Average income growth</td>
<td>-0.00191</td>
<td>-0.0136</td>
</tr>
<tr>
<td></td>
<td>(0.00175)</td>
<td>(0.00857)</td>
</tr>
<tr>
<td>Global systemically important banks</td>
<td>-0.699**</td>
<td>-0.500***</td>
</tr>
<tr>
<td></td>
<td>(0.306)</td>
<td>(0.190)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>3.927</td>
<td>3.927</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.275</td>
<td>0.163</td>
</tr>
</tbody>
</table>

Note: Socio-economic variables are observable only since 2011. The sample period is between 2011 and 2015. In column (2), we report between-$R^2$. Standard errors are in parentheses and clustered at bank level. * p < 0.10, ** p < 0.05, *** p < 0.01.
Table A.3: Regression Results (Heterogeneous Impact of Bank Capital by Bank Size)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk preference heterogeneity × Lagged risk weighted equity ratio</td>
<td>-0.991**</td>
<td>-0.922***</td>
</tr>
<tr>
<td></td>
<td>(0.465)</td>
<td>(0.320)</td>
</tr>
<tr>
<td>Lagged log total assets × Lagged risk weighted equity ratio</td>
<td>0.475***</td>
<td>0.547***</td>
</tr>
<tr>
<td></td>
<td>(0.169)</td>
<td>(0.143)</td>
</tr>
<tr>
<td>Risk preference heterogeneity</td>
<td>0.0723</td>
<td>0.0804</td>
</tr>
<tr>
<td></td>
<td>(0.0692)</td>
<td>(0.0533)</td>
</tr>
<tr>
<td>Lagged risk weighted equity ratio</td>
<td>-6.718***</td>
<td>-7.851***</td>
</tr>
<tr>
<td></td>
<td>(2.525)</td>
<td>(2.069)</td>
</tr>
<tr>
<td>Average risk preference</td>
<td>-0.0190*</td>
<td>-0.0170</td>
</tr>
<tr>
<td></td>
<td>(0.0103)</td>
<td>(0.0109)</td>
</tr>
<tr>
<td>Lagged log total assets</td>
<td>-0.794***</td>
<td>-0.707***</td>
</tr>
<tr>
<td></td>
<td>(0.220)</td>
<td>(0.162)</td>
</tr>
<tr>
<td>Lagged log total assets squared</td>
<td>0.0238***</td>
<td>0.0203***</td>
</tr>
<tr>
<td></td>
<td>(0.00748)</td>
<td>(0.00515)</td>
</tr>
<tr>
<td>Bank age</td>
<td>-0.00357</td>
<td>-0.00454***</td>
</tr>
<tr>
<td></td>
<td>(0.00237)</td>
<td>(0.000945)</td>
</tr>
<tr>
<td>Average HHI</td>
<td>0.163</td>
<td>0.0111</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>Average unemployment rate</td>
<td>-0.00523</td>
<td>-0.00616</td>
</tr>
<tr>
<td></td>
<td>(0.00733)</td>
<td>(0.00729)</td>
</tr>
<tr>
<td>Average income growth</td>
<td>-0.00199</td>
<td>-0.0174*</td>
</tr>
<tr>
<td></td>
<td>(0.00199)</td>
<td>(0.00951)</td>
</tr>
<tr>
<td>Global systemically important banks</td>
<td>-0.912**</td>
<td>-0.732***</td>
</tr>
<tr>
<td></td>
<td>(0.363)</td>
<td>(0.207)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>4,790</td>
<td>4,790</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.425</td>
<td>0.329</td>
</tr>
</tbody>
</table>

Note: In column (2), we report between-$R^2$. Standard errors are in parentheses and clustered at bank level. * p < 0.10, ** p < 0.05, *** p < 0.01.
3. Chapter 3: Information Sharing and Financial Fragility
Information Sharing and Financial Fragility

Guangqian Pan*

Abstract

In the presence of multiple equilibria, financial market may experience valuation shock which shifts the market from high credit supply equilibrium to low credit supply equilibrium, causing sharp declines in financing and welfare. This paper studies the impact of information sharing to this financial fragility. I find information sharing can mitigate the magnitude of the credit supply reduction; meanwhile increases market’s fragility, i.e. the likelihood of such reduction. Since information sharing encourages valuation and discourages unsophisticated investments, sophisticated investors would strictly prefer information sharing, which could lead to a suboptimal social outcome. From a social planner’s perspective, optimal choice of information sharing should be countercyclical.

Keywords: Information sharing; financial fragility; adverse selection; credit crunch; screening

JEL classification: D83 G01 G10 G21 G24 G28

---

* Guangqian Pan: College of Business and Economics, Australian Nation University, 26C Kingsley Street, Acton ACT 2601, Australia (e-mail: guangqian.pan@anu.edu.au). For helpful comments, I am particularly grateful to my supervisors, Phong Ngo (Chair), Kentaro Asai and Antje Berndt, and I thank Robert Marquez and Manju Puri. All views and remaining errors are my own.
3.1 Introduction

Banks are considered as special because of their ability to acquire and monitoring borrowers’ information [e.g. Diamond (1984)]. Recently, a wide range of regulator outside U.S. have implemented the so-called “open banking” regulation aiming to push banks to share their customers’ information. Few studies have examined how such information sharing on customers’ information can impact the stability of the financial system and the welfare implications. I explore this question in a setting of multiple valuation equilibria. Financial market may experience exogenous valuation shock which shifts the market from a high credit supply equilibrium to a low credit supply equilibrium, causing sharp declines in financing and welfare. I find information sharing can mitigate the magnitude of the credit supply reduction; meanwhile increases market’s fragility, i.e. the likelihood of such reduction. From a social planner’s perspective, an optimal choice of information sharing should be countercyclical. That is, in a booming period, limiting the likelihood of a crisis is important and not sharing information is optimal. Meanwhile, in a bust period, mitigating the magnitude of the crisis is important and sharing information is optimal.

To understand the welfare implications of information sharing, first we need to understand what information would be shared, to whom and why they would be shared. Let us consider two types of investors: sophisticated investors and unsophisticated investors, in a market providing finance to entrepreneurs holding either good projects or bad projects. Sophisticated investors have a special valuation technology to identify good projects and are able to extract information rent through costly valuation. Unsophisticated investors trade at a price which is determined by the expected quality of the leftover projects after sophisticated investors. The unsophisticated market serves as an outside option for good projects other than sophisticated investors’ offer. Sophisticated investors not only can benefit from their own valuation activity, they also benefit from other sophisticated investors’ valuation activities. The reason is
valuation performed by other sophisticated investors can worsen the leftover projects’ average quality in the unsophisticated market and lower the outside option price\(^1\).

To depart from the current literature, we consider the case where bad projects’ holders have the motivation to approach multiple sophisticated investors in hope of getting a higher price. This would reduce sophisticated investors’ valuation efficiency. To mitigate such dilution, sophisticated investors can share their valuation of bad projects to other sophisticated investors. For the rest part of this paper, we refer information sharing as this activity. Such information sharing brings two benefits to a sophisticated investor: [1] information sharing improves her own valuation efficiency, [2] when other sophisticated investors improve their valuation efficiency, they extract more good projects out of the market and lower the alternative cost for all sophisticated investors. Therefore, sophisticated investors would strictly prefer information sharing among themselves\(^2\). They will not share any information to unsophisticated market because that would filter some bad projects out of the unsophisticated market, increase price of outside options for good projects and raise the price to purchase good projects.

In the presence of multiple equilibria, financial market may experience valuation shock which shifts the market from high credit supply equilibrium to low credit supply equilibrium, causing sharp declines in financing and welfare [e.g. Fishman and Parker (2015); Gorton and Ordonez (2014)]. This paper studies the impact of information sharing to this financial fragility. I find information sharing can mitigate the magnitude of the credit supply reduction; meanwhile increases market’s fragility, i.e. the likelihood of such reduction. Since information sharing

\(^1\) Bolton, Santos, and Scheinkman (2016) discuss a similar mechanism in OTC market.

\(^2\) We assume sophisticated investors have full bargaining power against good asset holders and they don’t compete with each other as in Fishman and Parker (2015). Therefore, good asset holders will just sell project to the first sophisticated investor they encountered. This assumption eliminates the pricing impact due to sophisticated investors compete to get good assets. Nevertheless, the optimal information sharing may vary based on what information to share and what types of competition we model once we allow competition among sophisticated investors. For such discussion about the relationship between competition and information sharing, see Gal-Or (1985); Gal-Or (1986); Padilla and Pagano (1997).
encourages valuation and discourages unsophisticated investments, sophisticated investors would strictly prefer information sharing, which could lead to a suboptimal social outcome.

Our result also suggests a social planners’ choice of socially optimal information sharing should be countercyclical. It is not always socially desirable for sophisticated investors to share their information. While information sharing improves sophisticated investors’ valuation efficiency, it also amplifies the effect of valuation shock. When a proportion of sophisticated investors randomly start valuation, information sharing allows more good projects being identified, lowers alternative market’s project quality and encourages other sophisticated investors to start valuation as well. When all sophisticated investors choose to do valuation, it could create a market credit rationing and cut back aggregate credit supply [e.g. Fishman and Parker (2015)]. Therefore, in the presence of multiple equilibria, financial market is more likely to shift from high credit supply equilibrium to low credit supply equilibrium in the presence of information sharing. On the other hand, information sharing reduces duplicated valuation, allows more good projects being financed and increases social welfare in low credit supply equilibrium. Consequently, information sharing reduces the welfare drop from high credit supply equilibrium to low credit supply equilibrium. Overall, the social optimal level of information sharing depends on the trade-off between higher fragility to the valuation shock and lower welfare drop if the crisis occurs. When large shocks are rare, information sharing is less favorable since additional market fragility outweighs its benefit. However, when large shocks are more likely, information sharing’s amplifying effect of these shocks is bounded upside. Therefore, its mitigating welfare reduction role is more favourable and information sharing is socially desirable.

The ability to acquire information is commonly viewed as a key difference between sophisticated investors (e.g. banks) and unsophisticated investors (e.g. retail bond investors). For instance, financial intermediations are considered having expertise in screening [e.g. Chan,
Greenbaum, and Thakor (1986); Philippon (2015)]. Also, venture capitalists (VC) spend a significant amount of time and effort in screening [e.g. Kaplan and Stromberg (2001); Fried and Hisrich (1994)]. Moreover, VC involvements are positively related to firm’s innovation [e.g. Hellmann and Puri (2000); Kortum and Lerner (2000)]. Contrarily, in less sophisticated markets like peer to peer markets, screening rarely occurs (Einav, Farronato, & Levin, 2016).

On the other hand, welfare implication of information sharing is mixed. The proponents of information sharing argue it will reduce contract delinquencies and defaults, increase banks’ lending and profits, reduce the likelihood of financial crises and increase economic growth [e.g. Millon and Thakor (1985); Pagano and Jappelli (1993); Houston, Lin, Lin, and Ma (2010); Doblas-Madrid and Minetti (2013)]. Karapetyan and Stacescu (2014) show information sharing can encourage information acquisition, lead to better lending decisions and increase welfares. Nevertheless, Hertzberg, Liberti, and Paravisini (2011) study 1998 Argentine registry reform which forced lenders to share their borrowers’ negative assessments and find that information sharing could increase the occurrence of default for financial stressed firms by breaking down the coordination among lenders. Padilla and Pagano (2000) argue sharing default information can serve as a borrower discipline device in a moral hazard setting. Sharing past default could create best incentive for borrowers to perform. Either none sharing or sharing all information could destroy the lenders’ incentive to perform. While most of these papers examine the welfare effects of information sharing considering sophisticated investors, this paper contributes to the literature concerning both sophisticated markets and unsophisticated markets. With the inclusion of the unsophisticated market, we show that information sharing does not necessarily increase welfare and could depend on business cycle.

There are a range of literature explores how other forms of information acquisition in banking industry can impact financial stability. For instance, He and Manela (2016) explore how
depositors acquire private information about the bank when rumor occurs and the impact of such information acquisition to bank runs in a dynamic setting. They suggested providing public information of the bank solvency status can mitigate bank runs. Our paper differs from their paper since the information acquisition choices are made by banks. A credit crunch is created when the market only finances valued good projects, instead of creditors withdraw. Healthy banks can optimally choose such credit crunch in our setting.

Another relevant paper in the literature is Bouvard et al. (2015). In their paper, they explore the impacts of disclosure regulation on banks with rollover risk exposure. They find regulators would optimally increase transparency in banking industry to avoid systematic runs. This paper differs from their paper in two perspectives. First, unlike the Bouvard et al. (2015) explore the bank disclosure to outside investors, this paper looks at the information about the quality of the projects, which is shared among sophisticated investors are. Second, an important aspect of this paper is the presence of duel markets such that both sophisticated investors and unsophisticated investors can finance projects. Such examination of duel market is important to welfare implications since just looking one sophisticated market like banking industry can overlook the potential spillover effect of information sharing in alternative market.

3.2 Model setting

The baseline model of this paper is largely developed from Fishman and Parker (2015). There are two types of projects: good projects and bad projects. Good projects generate a return of \( R^g \) and bad projects generates a return of \( R^b \). All projects require investment of 1 to originate. The alternative cost of this investment would be the gross interest rate \( R \). We assume the bad projects are not profitable to invest and the good projects are. i.e. \( R^b / R < 1 < R^g / R \). It is a common knowledge that projects have a probability of \( \lambda \) being good in the market. There is a
unit mass of risk neutral sellers in the market, either holding good projects or bad projects and unaware of their project qualities ex ante.

There are 2 types of investors in the market: sophisticated investors and unsophisticated investors. Both types of investors are risk neutral. Sophisticated investors have access to limited valuation capacity and can use them at a cost of $c$ per unit. The number of sophisticated investors is finite denoted as $N$. Those sophisticated investors have an aggregate valuation capacity of $H$. Each sophisticated investor $i$ chooses to use $h_i$ unit of valuation capacity. For simplicity, we assume these sophisticated investors are homogenous. Sophisticated investors could correctly identify good projects$^3$ and only buy good ones right after the valuation$^4$.

**Key assumption:** Assume valuation capacity $H$ is not enough to value all projects$^5$.

This assumption is particularly important for those markets the underlying projects are too many to value (e.g. small business loan/consumer loans market) or relatively new industries where only a limited amount of human capitals/skills are available to assess the projects (e.g. start-up financing industry like venture capital).

A central piece where this paper departs from previous literature is that we explore the mechanism where information can be shared by sophisticated investors. When valuation is neither verifiable nor simultaneous, after a bad project holder gets rejected by a sophisticated investor, he/she still can approach another investor (either sophisticated or unsophisticated) for

---

$^3$ This assumption could be relaxed later in section 5.1 and the main result sustains.

$^4$ It is possible sophisticated investors buying unvalued assets when the expected return exceeds their origination cost. However, in that particular scenario, sophisticated investors are indifferent with unsophisticated investors. One may think of a case that sophisticated investors have two division operating differently with regard to their buying strategy. And we treat that one does value and buy as sophisticated investor and the other one as unsophisticated investor.

$^5$ Glode and Lowery (2016) emphasise the scarcity of financial experts’ labour supply in their study of financial experts’ compensations. This limited valuation capacity is also an important part of Fishman and Parker (2015)’s discussion. Nevertheless, this is not a crucial assumption for our result. In fact, this paper relaxed the valuation capacity assumption used in Fishman and Parker (2015). Even when sophisticated investors have valuation capacity to value all projects once, they could not value and buy all the good assets due to the dilution activities.
a sale. Sophisticated investor $i$ has a common belief he/she can identify $\lambda_i^*$ unit of good projects using one unit of valuation capacity. The information acquired by the sophisticated investor is the quality of the projects. Since good projects are purchased right away after the valuation, sharing such information will not change any decisions of market participant and therefore is trivial. On the other side, information sharing about valued bad projects is important for both sellers and buyers. The remaining part of paper, information sharing refers to the information about valued bad projects.

The key mechanism we will look at is closely associated with the bad projects’ holders’ incentive. The existence of unsophisticated investor market creates incentive for bad projects sellers to dilute sophisticated investors’ valuation capacity. By doing so, fewer good projects are valued and purchased by sophisticated investors aggregately. A portion of good projects are thus crowded out to pooling markets where the prices are set based on average quality. Consequently, the aggregate quality of the pooling market improves, and bad projects could be sold at a higher value. Due to the non-verifiable nature of valuation, sophisticated investors are unable to identify and punish this predatory behaviour. The only way to mitigate this predatory behaviour is through information sharing.

Unsophisticated investors are in a perfect competitive market. Therefore, the market is cleared in a break-even price $P^U$ for unsophisticated investors.

\[ P^U = w_u^g * (R^g / R) + w_u^b * (R^b / R) \]

The weights of good projects and bad projects $(w_u^g, w_u^b)$ in the pooling market depend on the valuation costs, prior quality and level of information sharing among sophisticated investors. On the other hand, sophisticated investors have all bargaining power against good projects sellers and will offer a price marginally higher than the alternative price offered by
unsophisticated investors or the origination cost. $P^S = \max\{1, P^U + \epsilon\}$. The expected profits for the sophisticated investor $i$ can be written as $E_i(\pi^S) = \max\{0, h_i[\lambda_i^* (R^9 / R - P^S) - c]\}$.

**Timing**

The timing of the events happens as the following. First, project holders approach sophisticated investors to get valued. The approaching process takes long enough so that those valued bad projects have sufficient time to go to all sophisticated investors. In the meantime, sophisticated investors decide the level of valuation capacity to use given certain level of information sharing (either exogenously decided by the regulator or endogenously chosen by sophisticated investor). Given the valuation capacity used, all participants have sufficient knowledge to form their beliefs of projects quality. Thus, prices are determined. Finally, market clears for both types of investors. Sophisticated investors will buy good projects if valuation occurs. Unsophisticated investors will buy the pooling projects if the return is attractive i.e. $P^U \geq 1$.

### 3.3 Exogenous information sharing level

Regardless of sophisticated investors’ willingness to share information or not, the actual sharing level may be constrained by frictions (e.g. searching costs or regulation). The result is a market can end up with partial or no information sharing. It is vital to look into how different level of information sharing may change social welfare and market stability. Here, we look at the case there is information sharing among sophisticated investors and no sharing to unsophisticated investors. We can derive four potential equilibria in the markets. We first

---

6 We focus on the sharing among sophisticated investors alone for two reasons. Firstly, the scenario that sophisticated investors only share information to unsophisticated investors but not to other sophisticated investors are unrealistic in application. Furthermore, even if that could be the case, bad projects holders will receive a constant price in pooling, and there is no incentive for them to waste valuation capacity at all. These two reasons can justify our focus on the sharing among sophisticated investors alone.
study the region of these equilibriums with regard to information sharing. Then, we
demonstrate how information sharing can change the social welfare in different ways.

3.3.1 Information sharing

Define \( \sigma \) be the level of information sharing among sophisticated investors which is
exogenously given. The valuation capacity that 1 unit of bad projects can occupy is \( 1 + (N - 1)(1 - \sigma) \). Note that if \( \sigma = 1 \), there is perfect information sharing. One unit of bad
projects maps exactly one unit of valuation capacity, and no dilution occurs. On the opposite
side, if \( \sigma = 0 \), there is no information sharing. One unit of bad projects will occupy \( N \) units of
valuation capacity which represents total number of sophisticated investors and the maximum
dilution level. Without information sharing, it takes every sophisticated investor to value the
same bad project once. If \( \sigma \) is anything between 0 and 1, this indicates a partial information
sharing. Since sophisticated investors are homogenous, they are able to identify a good project
at a posterior probability of \( \lambda^* \). The probability \( \lambda^* \) is depending on three components: the
aggregate prior probability of good projects \( \lambda \) in the market, the number of sophisticated
investors \( N \) and the information sharing level \( \sigma \).

\[
\lambda^* = \frac{\lambda}{\lambda + (1 - \lambda)(1 + (N - 1)(1 - \sigma))}
\]

Take the first order derivatives of \( \lambda^* \) with regard to these three drivers, we can get that:

\[
\frac{d\lambda^*}{d\lambda} > 0, \quad \frac{d\lambda^*}{dN} < 0, \quad \frac{d\lambda^*}{d\sigma} > 0
\]

The relationship between posterior probability and prior probability is positive since that the
higher aggregate market quality, the higher chance for sophisticated investors to get good
projects. The relationship between valuation efficiency and number of sophisticated investors
is negative since the more sophisticated investors a market has, the more difficult for them to
communicate and more bad projects will be valued ceteris paribus. The relationship between valuation efficiency and information sharing is positive since that the more information shared, the fewer valuation capacities are diluted by bad projects and more good projects will be identified.

3.3.2 Equilibrium

For all sophisticated investors to identify $\lambda$ unit of good projects, it will take $\lambda + (1 - \lambda)(1 + (N - 1)(1 - \sigma))$ unit of valuation capacity. Collectively, sophisticated investors choose an aggregate level of valuation $H$ given a limited cap $\bar{H}$. The valuation level $H$ is based on whether sophisticated investors find it profitable to do the valuation and provide finance. For the scenario $\bar{H} < \lambda + (1 - \lambda)(1 + (N - 1)(1 - \sigma))$, the sophisticated investors will either choose no valuation or use up all valuation capacity $\bar{H}$ in equilibrium. We assume the valuation capacity is not enough to value all projects. i.e. $\bar{H} < 1^\text{7}$. The profit constraint for sophisticated investors to do valuation is

$$[3] \quad E_i(\pi^S(P^U(H))) = h_i[\lambda^*_i(R^g / \max{R, 1, P^U(H)})] - c$$

On the other side, unsophisticated investors choose whether to invest into the rest of projects pool given $H$. Their prices are set as $P^U(H)$. Define the set of projects in Unsophisticated market be $\Phi^U$. The set of projects financed by sophisticated investors is $\Phi^g$. The set of good projects is defined as $\Phi^g$ and the set of good projects is defined as $\Phi^B$. $\lambda^*H$ units of good projects are expected to be identified (i.e. $|\Phi^g| = \lambda^*H$) and bought by sophisticated investors. The amount of project available in the unsophisticated market is $|\Phi^U| = 1 - |\Phi^g| = 1 - \lambda^*H$. That is unsophisticated investors face the rest of the projects pool with a size of $1 - \lambda^*H$.

Within those projects, all bad projects (i.e. $|\Phi^B| = 1 - \lambda$ unit of bad projects) and all unvalued

---

7 This assumption can be relaxed to $\bar{H} < \lambda + (1 - \lambda)(1 + (N - 1)(1 - \sigma))$ and all results still hold.
good projects \(|\Phi^g \setminus \Phi^g| = \lambda - \lambda^*H\) unit of good projects) are included. The trade constraint for unsophisticated investors to valuation is

\[
P^U(H) = \frac{(\lambda - \lambda^*H)R^g/R + (1-\lambda)R^b/R}{1-\lambda^*H} \geq 1
\]

Eventually, we will reach four types of equilibriums. We can distinguish these four equilibriums based on two criteria: 1. whether unsophisticated investors find pooling projects profitable and trade, 2. whether sophisticate investors find valuation profitable. Table 1 demonstrates how these two criteria define the four equilibriums. Alternatively, we can explore these criteria and rewrite them in term of valuation cost and quality as table 2\(^8\). We can show these equilibriums graphically in a quality-cost \((\lambda, c)\) plane as figure 1. Depend on the market quality and valuation cost, a region could have a unique equilibrium or two stable equilibrium coexists.

3.3.3 Welfare analysis

One key contribution of this paper is to compare the welfare under different levels of information sharing. To achieve this, we firstly calculate welfares under a given level of information sharing. Define social welfare \(V\) as the sum of the net value functions of all projects’ holders selling the projects and all investors financing the projects. Then, we can get the welfare of the four equilibriums as following:

\(^8\) See Appendix A.1 for the proof.
1. Pooling equilibrium:

\[ V^p = \frac{\lambda R_g + (1 - \lambda)R_b}{R} - 1 \]

2. No-Trade equilibrium:

\[ V^n = 0 \]

3. Pure valuation equilibrium:

\[ V^v = H(\lambda^* \left(\frac{R_g - R}{R}\right) - c) \]

4. Mixed equilibrium:

\[ V^m = \frac{\lambda R_g + (1 - \lambda)R_b}{R} - 1 - cH \]

The welfare of pooling equilibrium is the return when all projects are originated minus the origination cost 1. It is straightforward to see the welfare of no-trade equilibrium is 0 since no projects are financed. For pure valuation equilibrium, only sophisticated investors get positive profit which is the multiple of unit of valuation capacity used \( \bar{H} \) and the net profit per unit of valuation can gain is \( (\lambda^* \left(\frac{R_g - R}{R}\right) - c) \). For the mixed equilibrium, all projects are sold and sophisticated investors used \( \bar{H} \) units of valuation capacity at a cost of \( c \). Therefore, the aggregate welfare is the return from all projects minus the origination cost 1 and valuation costs \( c\bar{H} \). By comparing the welfare for different regions, we can find consistent results with Fishman & Parker (2015). In the regions of multiple equilibriums, pooling equilibrium gives higher welfare. Even in region of pure equilibrium, the strategy of buying all projects still can generate higher welfare. Mixed equilibrium is always less efficient than buying all projects,
since in addition to buying all projects, valuation costs are used by sophisticated investors as a tool to drive down the alternative cost. The more valuations are done, the less good projects in pooling and thus less alternative cost offered by unsophisticated investors. Valuation is a social waste and both good projects and bad projects holders bear the cost. Pure valuation equilibrium is always less efficient than pooling equilibrium in multiplicity since the benefit of including unvalued good projects and saved valuation costs outweigh the cost of originate bad projects in this region. In region that pure valuation equilibrium dominates, the strategy of buying all projects is more efficient as long as $c \geq c_{eff} = \frac{(1-\lambda^*H)R-(1-\lambda)R^B-(\lambda-\lambda^*H)R^B}{HR}$, i.e. $V^v \leq V^P$. This is illustrated as the region above the dotted line in figure 1.

The next step is comparing the welfares under different levels of information sharing. Without losing generality, we assume in the regions of multiple equilibria, equilibrium with valuation always dominates. Our result depends on whether there is an equilibrium shift. The cost constraints and the market quality constraints of equilibriums will change correspondingly with regard to information sharing and therefore shift the regions of all equilibriums. It is important to look back to table 2 and explore how those constraints change with regard to the information sharing. When $\sigma$ increases, more information is shared. Sophisticated investors’ valuation accuracy improves given less wastes occur, i.e. $\lambda^*$ increases. Given such improvement, the marginal benefit of using valuation would increase. Therefore, for equilibrium with valuation, the upper boundaries of valuation cost raise since they can afford higher valuation costs. No-trading equilibrium could shift to pure valuation equilibrium (region 4). Pooling equilibrium could shift to pure valuation equilibrium (region 1 and 2) or mixed equilibrium$^9$ (region 3). With regard to market quality constraints, the boundary between

---

$^9$ No trading equilibrium will never shift to a mixed equilibrium since lower boundary of mixed equilibrium’s market quality constraint is strictly higher than the upper boundary of no trading equilibrium’s market quality constraint.
pooling equilibrium and no trading equilibrium is independent of the information sharing. However, it will shift the boundary of market quality constraints between pure valuation equilibrium and mixed equilibrium towards left. The implication is that with more information sharing, the accuracy of valuation improves. Therefore, this leads to an overall increase in the size of good projects get valued and bought. Subsequently, the quality in unsophisticated market pool decreases. Unsophisticated investors may find the pooling projects are no longer profitable to originate and cease investments. This indicates a shift from mixed equilibrium to a pure equilibrium (region 7).

Notice that, only the welfare of pure valuation equilibrium depends on the information sharing. If there is no change of equilibrium type, increasing information sharing will only increase the welfare of pure equilibrium (region 5) since duplicated information acquisition is avoided. If there are changes in equilibrium type, there are four possibilities.

1. No-trade equilibrium to pure valuation equilibrium(region 4)
2. Pooling equilibrium to pure valuation equilibrium(region 1 and 2)
3. Mixed equilibrium to pure valuation equilibrium(region 7)
4. Pooling equilibrium to mixed equilibrium(region 3)

Unlike the no-trade equilibrium where no surplus is created, in pure valuation equilibrium sophisticated investors gain positive surplus. Therefore, a shift from no-trade equilibrium to pure valuation equilibrium will increase social welfare. The comparison of welfare in pooling equilibrium and welfare in pure valuation equilibrium is identical to previous single information sharing level case. For any valuation cost $c \geq c_{eff} = \frac{(1-\lambda^*\bar{H})R-(1-\lambda)R^b-(\lambda-\lambda^*\bar{H})R^g}{\bar{H}R}$,
the shift from pooling equilibrium to pure valuation equilibrium will decrease social welfare and vice versa. A shift from mixed equilibrium to pure valuation equilibrium will always increase the social welfare. And a shift from pooling equilibrium to mixed equilibrium will always decrease the social welfare since additional valuation costs occur. Figures 2 illustrates the overview for welfare changes comparing a partial information sharing regime and a complete information sharing regime. The green color indicates the regions have an increase in social welfare after information sharing shift from partial sharing to complete sharing. The red color indicates the regions have a decrease in social welfare after information sharing shift from partial sharing to complete sharing. The white regions are those social welfares stay unchanged. In summary, we will get Proposition 1 as following.  

Proposition 1

Assume in the region of multiple equilibriums, equilibriums with valuation always dominate. When \( c \geq c^{eff} \), perfect information sharing will decrease the social welfare for regions switching from pooling equilibrium to equilibrium with valuation. The rest of valuation region will have an increase or keep unchanged in social welfare.

One noticeable result is that for those regions shift from pooling equilibrium to valuation regimes and \( c \geq c^{ef} \), the social welfare actually decreases. Unlike previous literature social inefficiency is caused by competition among sophisticated investors, here the social inefficiency is caused when sophisticated investors become interested in acquiring information at the cost of other market participants. This is because when information sharing improves, it creates the incentive for all sophisticated investors to do valuation. When valuation leads to the positive surplus for them, it reduces the overall social welfare since the cost of valuation and cost of passing away good projects due to limited valuation capacity exceeds the profit of

---

See Appendix A.2 for the proof.
avoiding bad projects at aggregate level. However, the sophisticated investors only care if the profits from good projects are sufficient to cover the cost of valuation. They don't care passing away unvalued goods projects since they know the valuation capacity is limited at the first place.

3.3.4 Impacts of valuation shocks

Fishman & Parker’s (2015) states in the region of multiplicity, shifts from pooling equilibrium to a pure valuation equilibrium/mixed equilibrium have the feature of credit crunch: lower financing, lower price, lower social welfare etc. And they mention the shift can be triggered by non-fundamental shocks without specifically identify what are these shocks. In this section, we specify the shocks as exogenous irrational valuation shocks. Without the shock, pooling equilibrium is a stable equilibrium where all sophisticated investors will choose not to value since the alternative cost is too high and the net profit from valuation is not enough to cover it. When a small proportion of sophisticated investors start to value, it drives down the competitive costs from pooling market. Other sophisticated investors will find valuation is profitable and start to do valuation. Collaboratively sophisticated investors will maximize their usage of valuation capacity. If the rest of the projects pool is still attractive for unsophisticated investors to invest, the market shifts from pooling equilibrium to mixed equilibrium, otherwise, the market shifts from pooling equilibrium to pure valuation equilibrium. There are two key elements we care about in such shift. Firstly, we care about the size of the shock can cause a shift. The smaller the shock is needed, the more vulnerable the market is and we should expect the shift easier to happen. Secondly, we care the magnitude of the drop in social welfare. It measures the negative impact of such shift.
Next, we explore how different levels of information sharing will impact the vulnerability of the market and outcome of the shock. The results are stated in Proposition 2 and Proposition 3 with regard to two possible types of the shift.

**Proposition 2**

A shift from pooling equilibrium to pure valuation equilibrium causes a drop in social welfare. By increasing information sharing, the size of such social welfare drop decreases. In exchange of this, the shift can be triggered by a smaller valuation shock. Increasing information sharing does not impact the size of price drop, but does reduce the rationing in financing.

The proof of the proposition 2 is achieved by exploring the mechanism that how a non-fundamental valuation shock triggers a drop. Here, we would look at a given point \((\hat{\lambda}, \hat{e})\) within the region that pooling equilibrium and pure valuation equilibrium coexists. We assume the market is in a pooling equilibrium in the first place. The sophisticated investors’ profits, market price and aggregate welfare are depending on the level of valuation capacity \(H\) used. The relationship can be illustrated in figure 3. The more valuation is done, the less good projects in unsophisticated investors’ project pool and the price \(P_U\) will drop. The social welfare drops constantly as long as unsophisticated investors still trade (i.e. \(P_U(H) > 1\)). The valuation creates pure social waste since all projects are purchased eventually. More valuation leads to lower social welfare. However, when the valuation exceeds certain point (i.e. \(P_U(H) \leq 1\)), unsophisticated investors no longer trade since the cost of origination exceeds profits. In this case, the social welfare equals to sophisticated investors’ profits. Given the marginal profit of

\[\lambda \text{satisfies the market quality constraints: } \frac{R - R^b}{R^g - R^b} \leq \lambda \leq \hat{\lambda}. \hat{e} \text{satisfies the cost constraints: } \frac{\lambda'(1-\lambda)(R^g - R^b)}{R} \leq \hat{e} \leq \frac{\lambda'(R^g - R^b)}{R}\]

\[11 \, \hat{\lambda} \text{ satisfies the market quality constraints: } \frac{R - R^b}{R^g - R^b} \leq \lambda \leq \hat{\lambda}. \hat{e} \text{satisfies the cost constraints: } \frac{\lambda'(1-\lambda)(R^g - R^b)}{R} \leq \hat{e} \leq \frac{\lambda'(R^g - R^b)}{R}\]

\[12 \, \text{The reverse shift can be interpreted as a recovery from a crisis and the underlying idea is similar to what we proposed in this paper.}\]
valuation exceeds the marginal cost, social welfare maximizes locally when \( H = 0 \). Therefore, \( H = \bar{H} \) and \( H = 0 \) are the two stable equilibriums, representing pure valuation equilibrium and pooling equilibrium respectively.

Both pooling equilibrium and pure valuation equilibrium are stable equilibrium that sophisticated investors have no incentive to deviate away. Therefore, a shift from pooling equilibrium to pure valuation equilibrium requires a sizable aggregate valuation shock to make valuation attractive. The minimum size of such a valuation shock is \( \bar{H} \) which satisfy the following condition.

\[
\bar{H} = \frac{1 - \frac{\lambda^*(1-\lambda)(B^b - B^b)}{cR}}{\lambda^*}
\]

Here, \( \bar{H} \) is a measure of market vulnerability. The smaller \( \bar{H} \) is, the more vulnerable a market to valuation shock. \( \bar{H} \) decreases with regard to \( \lambda^* \)\(^{13}\). Consequently, we can conclude that information sharing increases the efficiency of valuation and increases market’s vulnerability. The intuition is as following. The reason valuation shock can make valuation profitable is that by extracting sizable good projects from unsophisticated market and driving down the alternative option price. This can be done more efficiently if the valuation accuracy is improved through information sharing. It's a good thing for sophisticated investors since they can make positive profits, but at the cost of extracting all other market participants’ surplus and creates social inefficiency. On the other hand, information sharing increases the welfare of pure valuation equilibrium without changing the welfare of pooling equilibrium. Therefore, the welfare drop from pooling equilibrium to pure valuation equilibrium narrows. With regard to

\(^{13}\) See Appendix A.3 for the proof.
the price, the drop will be constant (from \( \frac{\lambda R^\theta + (1-\lambda) R^b}{R} \) to 1). The drop of total investment narrows since more good projects are identified and financed given shared information. The changes are illustrated in Figure 4.

[Insert Figure 4]

For the region pooling equilibrium and pure valuation equilibrium coexist, the optimal choice of information sharing is decided by the trade-off between increase in market vulnerability to valuation shocks and decrease in the magnitude of social welfare drop caused by such shock. A decision can be justified by choosing the lowest expected drop of shocks as we will discuss in next subsection.

Proposition 3

A shift from pooling equilibrium to a mixed equilibrium causes a drop in social welfare. By increasing information sharing, the size of such social welfare drop does not change. However, the shift would be triggered by a smaller valuation shock. The price drop is more sever given more information shared.

[Insert Figure 5]

The mechanism triggers the shift from pooling equilibrium to the mixed equilibrium is similar. Here, we would look at a given point \((\hat{\lambda}, \hat{c})\) within the region of pooling equilibrium and mixed equilibrium coexists\(^{14}\). Again, we assume the market is in a pooling equilibrium in the first place. The relationship can be illustrated in Figure 5. Both pooling equilibrium and mixed equilibrium are stable equilibrium that sophisticated investors have no incentive to deviate

\(^{14}\) \(\hat{\lambda}\) satisfies the market quality constraints: \(\hat{\lambda} \geq \hat{\lambda}\). \(\hat{\lambda}\) satisfies the cost constraints:

\[
\frac{\lambda^*(1-\lambda)(R^\theta-R^b)}{R} \leq \hat{c} \leq \frac{\lambda^*(1-\lambda)(R^\theta-R^b)}{(1-\lambda^*H)R}
\]
away. $\tilde{H}$ is the measure of market vulnerability. The smaller $\tilde{H}$ is, the more vulnerable a market to valuation shock. $\tilde{H}$ decreases with regard to $\lambda'$. Consequently, we can conclude that information sharing increases the accuracy of valuation and increases market’s vulnerability. The intuition is similar as the scenario in Proposition 4. Sophisticated investors can make higher profits in mixed equilibrium when information is better shared at the cost of extracting all other market participants’ surplus and create social inefficiency. However, the welfare in mixed equilibrium is independent of information sharing. Therefore, the aggregate welfare drop does not change in this case but the wealth transfers from other participants to sophisticated investors are higher. With complete information sharing, the price drop increases since more good projects are taken (from $\frac{\lambda R^b + (1-\lambda)R^g}{R}$ to $\frac{(\lambda - \lambda'H)R^b/R + (1-\lambda)R^g/R}{1-\lambda'H}$). There is no investment drop since all projects are originated regardless information sharing. For the region pooling equilibrium and mixed equilibrium coexist, the optimal choice of information sharing is always no information sharing since information sharing increases market vulnerability without changing the welfare drop. The changes are illustrated in Figure 6.

[Insert Figure 6]

3.3.5 Optimal information sharing level

With the trade-off realized in Proposition 4, eventually we want to know the optimal level of information sharing to lessen the expected drop $\tilde{D}$ and to mitigate the impact of financial fragility. As we previously discussed, the expected drop $\tilde{D}$ will depend on two elements: the probability of such event happens and the size of drop if it occurs. We already know any valuation shock $\tilde{H}$ beyond the size of $\tilde{H}$ will trigger the shift of equilibrium and $\tilde{H} \in [0, \tilde{H}]$. Define the probability of $\alpha_i$ that each sophisticated investor $i$ may start to do valuation. Assume these $\alpha_i$ are independent and identically distributed following $f(\alpha)$. Let $\alpha = \frac{\tilde{H}}{\tilde{H}}$, then
we have $\alpha \in [0,1]$. The distribution of $\alpha$ is defined by its probability density function $f(\alpha)$ and its cumulative distribution function $F(\alpha)$. The probability of a shift will be triggered is $1 - F(\alpha)$. On the other hand, the size of drop if happens is $D$. It measures the difference of welfare in pooling equilibrium and the welfare in pure valuation equilibrium. Therefore, we have:

$$D = V^p - V^v = \frac{\lambda R^g + (1 - \lambda)R^b}{R} - 1 - \bar{H}(\lambda^* \left(\frac{R^g - R}{R}\right) - c)$$

Combine with equation 5, we can get the expected drop $\bar{D}$.

$$\bar{D} = (1 - F \left(1 - \frac{1}{\sqrt{\frac{\lambda^*(1-\lambda)(R^g - R^b)}{cR}}\frac{\lambda^* R^g + (1-\lambda)R^b}{R} - 1 - \bar{H}(\lambda^* \left(\frac{R^g - R}{R}\right) - c)}\right)$$

Overall, a decrease in $\sigma$ indicates a decrease in information sharing level. The vulnerability of the market decreases (i.e. $\bar{H}$ increases and $1 - F(\alpha)$ decreases). Therefore, the shift is less likely. On the other hand, the drop $D$ will be higher. Figure 7 illustrates the changes in minimum shock required $\bar{H}$ and drop $D$ with regard to information sharing level $\sigma$.

As figure 8 shows, the optimal level of information sharing will depend on the distribution of $\alpha$. We simulate the expected drops in social welfare under different types of distributions $f(\alpha)$. If the distribution weighs heavily in left tail (i.e. the market could easily shift to a low credit supply equilibrium like a recession period), the increase in probability will be trivial compare to decrease in the downside risk. Therefore, an increase in information sharing level $\sigma$ could decrease the expected drop $\bar{D}$ under this scenario (Recession in figure 8). If the distribution weighs heavily in right tail (i.e. the financial fragility is low like a booming period), the increase in crisis probability will significant enough to outweigh the decrease in
the downside risk. Therefore, an increase in $\sigma$ could increase the expected drop $\bar{D}$ (Boom in figure 8).

Other than business cycles, our result can also explain why countries differ in their choice on public information sharing since the optimal choice may rely on how likely the valuation shocks may happen in each country. In countries valuation shocks rarely happen, less information sharing may be favourable. In contrast, in countries valuation shocks are highly systematic and in large scales, complete information sharing may be the optimal choice

[Insert Figure 8]

3.4 Information sharing as a choice

Now, we consider the case that the information acquirers (sophisticated investors) have the choice of whether to share information to the other sophisticated investors or to those can’t acquire information at all (unsophisticated investors). Define the set of all goods as $\Phi$. The set of good projects is $\Phi^g$ and the set of bad projects is $\Phi^b$. Then, we can get $\Phi = \{\Phi^g, \Phi^b\}$. Define set of projects sophisticated investor $i$ valued as $\Phi^S_i$. Within these projects, there are good ones (denote as set $\Phi^g_i$) and bad ones (denote as set $\Phi^b_i$). i.e. $\Phi^S_i = \{\Phi^g_i, \Phi^b_i\}$. Since good projects are bought right away by sophisticated investors after valuation, $\Phi^g_i$ s are mutually exclusive. However, $\Phi^b_i$ s may or may not be mutually exclusive depend on the level of information sharing. The set of valued good projects is $\Phi^g$ and the set of valued bad projects is $\Phi^b$. Then, we have $\Phi^g = \bigcup_{i=1}^N \Phi^g_i, \Phi^b = \bigcup_{i=1}^N \Phi^b_i$. Different sophisticated investors may value the same bad projects given an imperfect information sharing. Let $su$ be a dummy variable whether sophisticated investors share their information with unsophisticated investors. Define $\Phi^b(su)$ as the set of bad projects have been valued by sophisticated investors and still able to sell in unsophisticated investors’ pool due to transparency problem. If $su = 0$, there is
no information sharing from sophisticated investors to unsophisticated investors, therefore, all bad projects valued by sophisticated investors will still be sold in unsophisticated investors’ pool. On the other hand, if $su = 1$, all valued bad projects are known to unsophisticated investors and they will be rejected directly. Thus, $\Phi^b(su) = \Phi^b$ if $su = 0$ and $\Phi^b(su) = \emptyset$ if $su = 1$. Define set of projects unsophisticated investors face as $\Phi^U$. We can separate the set into three groups: unvalued good projects ($\Phi^G \setminus \Phi^g$), unvalued bad projects ($\Phi^B \setminus \Phi^b$) and valued bad projects in the pool $\Phi^b(su)$. i.e. $\Phi^U = \{\Phi^G \setminus \Phi^g, \Phi^B \setminus \Phi^b, \Phi^b(su)\}$. The weights of good projects and bad projects could be written as $w^U_g = \frac{|\Phi^G \setminus \Phi^g|}{|\Phi^U|}$ and $w^U_b = \frac{|(\Phi^B \setminus \Phi^b) + \Phi^b(su)|}{|\Phi^U|}$.

We consider valuation as a mechanism mapping projects to good projects and bad projects. $h_i: \Phi^S_i \rightarrow \{\Phi^g_i, \Phi^b_i\}$.

The number of valuation capacity used equals to the size of valued projects. i.e. $h_i = |\Phi^S_i|$.

Then, we study the optimal choice for sophisticated investors in choosing information sharing level. The results are demonstrated in proposition 4 and proposition 5.

**Proposition 4**

In any equilibrium involves valuation, sophisticated investors prefer sharing information to other sophisticated investors than not sharing\(^\text{15}\).

The intuition is as following. Sophisticated investor $i$ shares information to another sophisticated investor $j$ can decrease $j$’s dilution on valuation capacity. The freed valuation capacity for $j$ can identify more good projects. It will lower the quality of the pooling market and thus lower alternative cost for the sophisticated investor $i$ needs to pay. Therefore, even sharing information to other sophisticated investors will not improve a sophisticated investor’s valuation accuracy, it can reduce the cost he pays thus increases the profit. Therefore,

---

\(^{15}\) See Appendix B.1 for the proof.
sophisticated investors always prefer to do so. In equilibrium, every sophisticated investor will share their information with others.

*Proposition 5*

Sophisticated investors prefer not sharing information to other unsophisticated investors than sharing\(^{16}\).

The disincentive of sharing information to unsophisticated investors is also related to the alternative cost. Sharing information to other unsophisticated investors can help unsophisticated investors filters out those bad projects in the pooling market. This would improve the quality of unsophisticated investors can get and increase the price they would like to offer. Thus, it simply increases sophisticated investors’ alternative cost. Therefore, in equilibrium, no sophisticated investors will share their information with unsophisticated investors.

Our results fit the reality quite well in a sense that there is an increasing trend for countries globally introducing private credit agent as documented in Jappelli & Pagano’s (2002) paper. However, as far as we know, there are no single policy favouring the information sharing between sophisticated investors and unsophisticated investors.

### 3.5 Discussions

#### 3.5.1 Noisy valuation

In the main model, we assume the valuation technique would be perfect. That is sophisticated investors could always correctly identify the good projects and reject bad projects. In this section, we will relax this assumption and allow sophisticated investor to make valuation errors. This would create additional incentive for the bad projects holders to approach other

\(^{16}\) See Appendix B.2 for the proof.
sophisticated investors after rejected in a valuation. Multiple rounds of valuation increase their chances for bad projects misidentified as good projects. Nevertheless, our result is robust to this change\textsuperscript{17}. The key difference here is information sharing will incur additional social benefit since it mitigates misidentification of bad projects.

3.5.2 Costly dilution

In the main model, we also assume it is cost-free for bad project holders to approach another sophisticated investor. Given this assumption, bad project holders would approach all the sophisticated investors to dilute their valuation. Nevertheless, it could be costly for those bad project holders to approach another sophisticated investor. The examples of the costs could include the fees and time spent for each loan application or searching costs for project holders to find a sophisticated investor.

Assume there is a fixed cost $k$ for sellers to get valuation. Therefore, bad project holders choose their level of dilution based on the trade-off between the cost $k$ and the marginal benefit from rising price in pooling market. Project holders will face a diminishing return on dilution. The more dilution they create, fewer additional good projects are crowded out. The marginal benefit for the dilution eventually will exceed the fixed cost of dilution. In this case, bad project holders will only approach optimal number of sophisticated investors. Consequently, putting a cost on valuation for project holders can limit the scale of dilution and reducing the benefit of information sharing. Nevertheless, it also reduces the incentive for projects holders to seek finance.

\textsuperscript{17} See Appendix C for the proof.
3.5.3 Start-up financing

While our primary goal is studying the banking system, the model could be applicable to other financing topics like start-up financing. Consider there are two markets for start-up entrepreneurs to seek financing: a sophisticated investors’ market, e.g. venture capitalists, and an unsophisticated investors’ market, e.g. online equity crowd funding platform like Kickstarter. In the venture capital [VC] market, there are $N$ sophisticated venture capitalists with identical valuation techniques can identify good projects and provide financing to those projects. In Kickstarter, those leftover projects [both unvalued projects and rejected bad projects in VC market] are financed by unsophisticated investors at a pooling price. The venture capital market has limited valuation capacity, thus cannot value all projects. Entrepreneurs have been identified with bad projects by one venture capitalist have incentives to approach other venture capitalists and get valued again\(^{18}\). This behaviour dilutes venture capitalists’ valuation efficiencies, lowers the fraction of good projects being identified in the VC market and increases the over quality and price of leftover projects in Kickstarter. Venture capitalist can mitigate such dilutions by sharing bad projects’ identity among each other.

3.6 Conclusion

This paper explores the welfare implication of information sharing under the framework of multiple equilibria setting triggered by the sophisticated investors’ information acquisition choice. The source of the financial fragility: information acquisition is particularly important in this setting since whether or not sophisticated investors choose to acquire information about the quality of the projects determines the credit supply of the financial system and social

---

\(^{18}\) Marquez (2002) discusses a similar setting and suggests “Since information is proprietary and not transferable,” bad borrowers identified by one bank “remain as part of the pool of customers that are unknown to all other banks.” When banks have limited lending capacity, more banks lead to information dispersion and more bad firms get financed.
welfare. Information sharing shapes the efficiency of information acquisition and thus has fundamental impact on the financial fragility through this mechanism.

Specifically, information sharing encourages information acquisition by improving its efficiency. Sophisticated investors would favor information acquisition when all their information would be shared. This increases the likelihood for the financial market to cut back credit supplies and only providing financing to limited good projects through information acquisition. In this perspective, information sharing increases the financial fragility. Meanwhile, since the information acquisition efficiency improves, more good projects will be identified and financed through information acquisition. Therefore, the welfare drop in a credit tightening regime will be smaller when information is shared.

This trade-off implies asymmetric optimality of information sharing in different stages of business cycles. In a booming period, the starting probability of a credit crunch is low. Information sharing could significantly increase the likelihood of a credit crunch and would not be desirable. However, in a recession period, the probability of credit tightening in the market is high and information sharing would be more favorable given it mitigates the welfare loss in the event of credit crunch. Therefore, the optimal information sharing policy should be countercyclical.
3.7 Reference


3.8 Appendix

3.8.1 Appendix A

A.1 Equilibriums constraints

1. Pooling equilibrium:

As stated in table 1, the key feature of pooling equilibrium is \( P^U (H) > 1 \) and \( E_i(\pi^S (P^U (H))) \leq 0 \). Valuation is not profitable but pooling trade is. As a result, no valuation is done by sophisticated investors. i.e. \( H = 0 \). Substitute this into equation 4, we can get:

\[
P^U (H) = \frac{\lambda R^g + (1-\lambda) R^b}{R} > 1
\]

Rewrite equation 7 in term of market quality \( \lambda \), we can get the Market quality constraint:

\[
\lambda > \frac{R - R^b}{R^g - R^b}
\]

With regard to the valuation cost, given equation 7, equation 3 should write as

\[
E_i(\pi^S (P^U (H))) = h_i[\lambda^* (R^g / R - \frac{\lambda R^g + (1-\lambda) R^b}{R}) - c] \leq 0
\]

Reorganize equation 8, we can get the Cost constraint:

\[
c \geq \frac{\lambda^* (1 - \lambda) (R^g - R^b)}{R}
\]

2. No-trade equilibrium:

The key feature of pooling equilibrium is \( P^U (H) \leq 1 \) and \( E_i(\pi^S (P^U (H))) \leq 0 \). Neither Valuation nor pooling trade is profitable. As a result, no valuation is done by sophisticated investors, i.e. \( H = 0 \). Substitute this into equation 4, we can get:

\[
P^U (H) = \frac{\lambda R^g + (1-\lambda) R^b}{R} \leq 1
\]

Rewrite equation 9 in term of Market quality \( \lambda \), we can get the Market quality constraint:

\[
\lambda \leq \frac{R - R^b}{R^g - R^b}
\]

With regard to the valuation cost, given equation 9, equation 3 should write as

\[
E_i(\pi^S (P^U (H))) = h_i[\lambda^* (R^g / R - 1 ) - c] \leq 0
\]
Reorganize equation 10, we can get the cost constraint:

$$c \geq \frac{\lambda^*(R^\theta - R^b)}{R}$$

3. Pure valuation equilibrium:

The key feature of pooling equilibrium is $P^U(H) \leq 1$ and $E_t(\pi^S(P^U(H))) > 0$. Valuation is profitable but pooling trade is not. As a result, valuation is maximized by sophisticated investors. i.e. $H = \bar{H}$. Substitute this into equation 4, we can get:

\[11\]

$$P^U(H) = \frac{(\lambda - \lambda^*\bar{H})R^\theta / R + (1 - \lambda) R^b / R}{1 - \lambda^* \bar{H}} \leq 1$$

Substitute equation 2 into equation 11 and reorganize in term of Market quality $\lambda$, we can get the Market quality constraint:

$$\lambda \leq \bar{\lambda}$$

Where $\bar{\lambda}$ is the solution of quadratic function

$$\frac{\lambda}{1 - \lambda^* \bar{H}} = \frac{R^b - R}{R^\theta - R^b}.$$

$$\bar{\lambda} = \frac{R - R^b + R^\theta \bar{H} - R\bar{H} + (2R^b - R^\theta - R)(1+\lambda)(1+\lambda)}{2(R^b - R^\theta)(1+\lambda)}$$

With regard to the valuation cost, given equation 11, equation 3 should write as

\[12\]

$$E_t(\pi^S(P^U(H))) = h_t[\lambda^*(R^\theta / R - 1) - c] > 0$$

Reorganize equation 10, we can get the Cost constraint:

$$c < \frac{\lambda^*(R^\theta - R^b)}{R}$$

4. Mixed equilibrium:

The key feature of pooling equilibrium is $P^U(H) > 1$ and $E_t(\pi^S(P^U(H))) > 0$. Both Valuation and pooling trade is profitable. As a result, valuation is maximized by sophisticated investors. i.e. $H = \bar{H}$. Substitute this into equation 4, we can get:
\[ P^U(H) = \frac{(\lambda - \lambda^*)R^g/R + (1 - \lambda)R^b/R}{1 - \lambda^*H} > 1 \]

Substitute equation 2 into equation 13 and reorganize in term of Market quality \( \lambda \), we can get the Market quality constraint:

\[ \lambda > \bar{\lambda} \]

With regard to the valuation cost, given equation 13, equation 3 should write as

\[ E_i(\pi^v(P^U(H))) = h_i \left[ \lambda^* \left( R^g/R + \frac{(\lambda - \lambda^*)R^g/R + (1 - \lambda)R^b/R}{1 - \lambda^*H} \right) - c \right] > 0 \]

Reorganize equation 14, we can get the Cost constraint:

\[ c < \frac{\lambda^*(1 - \lambda)(R^g - R^b)}{(1 - \lambda^*H)R} \]

A.2 Proof of proposition 1

Assume in the region of multiple equilibriums, equilibriums with valuation always dominate. When there is information sharing regime change, there are nine regions we may care about. There are regions of no-trading equilibrium and pooling equilibrium both before and after the regime change. The rest regions are numbered as 1 to 7 in figure 2.

Region 1: from pooling equilibrium to pure valuation equilibrium and \( c \geq c^{eff} \).

We have when \( c \geq c^{eff} \), \( V^p_{old} = V^p_{new} \geq V^p_{new} \). The social welfare decreases.

Region 2: from pooling equilibrium to pure valuation equilibrium and \( c \leq c^{eff} \).

We have when \( c \leq c^{eff} \), \( V^p_{old} = V^p_{new} \leq V^p_{new} \). The social welfare increases.

Region 3: from pooling equilibrium to mixed equilibrium.

Since \( V^p_{old} = V^p_{new} \geq V^m_{new} \), the social welfare decreases.

Region 4: from no trading equilibrium to pure valuation equilibrium.

Since \( V^n_{new} > 0 = V^n_{old} \), the social welfare increases.
Region 5: from pure valuation equilibrium to pure valuation equilibrium.

Since $V_{new}^v > V_{old}^v$ ($V^v$ decrease in $\sigma$), the social welfare increases.

Region 6: from mixed equilibrium to mixed equilibrium.

Since $V_{new}^m = V_{old}^m$, the social welfare stay unchanged.

Region 7: from mixed equilibrium to pure valuation equilibrium.

Since $V_{new}^v > V_{new}^m = V_{old}^m$, the social welfare increases.

A.3 Proof of proposition 2

For sophisticated investors, they are the one choosing the amount of valuation capacity to use. They are maximizing their profit $\pi^S(P^U(H)) = H[\lambda^*(R^\theta/R - \max\{1, P^U(H)\}) - c]$ where

$$P^U(H) = \frac{(\lambda - \lambda^*H) R^\theta / R + (1 - \lambda) R^b / R}{1 - \lambda^*H}$$

Assume sophisticated investors will always originate, then $\pi^S(P^U(H)) = H[\lambda^*(\frac{(\lambda - \lambda^*H) R^\theta / R + (1 - \lambda) R^b / R}{1 - \lambda^*H}) - c]$. It's a curved function with minimum obtained at $\tilde{H}$.

$$\tilde{H} = \frac{1 - \sqrt{\lambda^*(1 - \lambda)(R^\theta - R^b)}}{\lambda^*cR} > 0$$

Take the first derivative of $\tilde{H}$ with regard to $\lambda^*$,

$$\frac{d\tilde{H}}{d\lambda^*} = 0.5 \sqrt{\frac{\lambda^*(1 - \lambda)(R^\theta - R^b)}{cR \lambda^*^2}} - 1 < 0$$

Therefore, $\tilde{H}$ decreases with regard to $\lambda^*$. And $\lambda^*$ increases with regard to $\sigma$, so information sharing decreases $\tilde{H}$. 
3.8.2 Appendix B

B.1 Proof of proposition 4

We can have the size of unsophisticated investors’ projects pool be $|\Phi^u|$.

$$|\Phi^u| = |\Phi^g \setminus \Phi^g| + |\Phi^b \setminus \Phi^b| + |\Phi^b(su)| = (|\Phi^g| - |\Phi^g|) + (|\Phi^b| - |\Phi^b|) +$$

$$|\Phi^b(su)| = 1 - |\Phi^g| - (|\Phi^b| - |\Phi^b(su)|).$$

Sharing information to sophisticated investor frees $H_i$ units of valuation capacity for other sophisticated investors.

$$H_i = \sum_{j \neq i} |\Phi_j^b \cap \Phi_i^b| \geq 0$$

The freed valuation capacity would be used identify more good projects for other sophisticated investors, i.e. increase $|\Phi^g|$ and $|\Phi^b|$. For $su = 1$, $P_U$ will be constant $P_U = \frac{\lambda_D^b + (1-\lambda)D_b}{R}$. For $su = 0$, $w^g_U$ decreases with regard to $|\Phi_b(su)|$. Therefore, information sharing will increase $w^g_U$, increase $P_U$ and decrease $E_i(\pi_S)$.

$$w^g_U = \frac{|\Phi^g| - |\Phi^g|}{1 - |\Phi^g|}$$

B.2 Proof of proposition 5

Sharing information to unsophisticated investor will help them exclude $\Phi_i^b$ out of pool and the bad projects in the pooling strictly decrease. Less valued bad projects $\Phi^b(su)$ enter pool, i.e. from $\Phi^b$ to 0. $w^b_U$ decreases with regard to $|\Phi^b(su)|$. Therefore, information sharing will increase $w^b_U$, increase $P_U$ and decrease $E_i(\pi_S)$.

$$w^b_U = \frac{|\Phi^g| - |\Phi^g|}{1 - |\Phi^g| - (|\Phi^b| - |\Phi^b(su)|)}$$
3.8.3 Appendix C: Noisy valuation

Sellers

There exists one-unit mass of entrepreneurs whom is unsure about their project quality. Each entrepreneur holds one unit of goods. Among those projects, \( \lambda \) of them are good projects and the rest \( 1 - \lambda \) of them are bad projects, whereas \( \lambda \in (0,1) \). All projects need a cost of 1 to initiate. A good project will generate a gross return of \( g \) and a bad project will generate a gross return of \( b \). The gross interest rate is \( R \). We assume the good projects are worth investing and bad projects are not. Therefore, we have \( \frac{b}{R} < 1 < \frac{g}{R} \). Entrepreneurs can sell those projects in two markets: one market only sophisticated investors will participate; the other market unsophisticated investors will participate.

Buyers

In the sophisticated market, there are \( N \) identical investors in the market, whereas \( N > 1 \). Sophisticated investors hold the technology to assess the quality of projects, which we call valuation for the rest part of the paper. Valuation is non-verifiable by outsiders other than the buyer and seller pair. Moreover, the technology assesses the project quality with a noise \( \varepsilon \). That is sophisticated investor would identify a good (bad) project as a bad (good) project with a probability of \( \varepsilon \). We assume \( \varepsilon < \frac{1}{2} \) (i.e. sophisticated investors have relatively accurate technology). Sophisticated investors buy a project at price \( P^S \) if they are identified as a good project. Projects which are identified as bad projects will be rejected by the sophisticated investor assessed them. Sophisticated investors have a valuation capacity \( c \) which only allows them to aggregately assess \( H \) units of projects. All sophisticated investors can use their valuation capacity at a cost of \( c \) per unit. Assume the valuation capacity \( H \) is not enough to assess all projects. i.e. \( H < 1 \). For the sophisticated investors, they decide the individual level of the valuation \( h_i \). Aggregately, sophisticated investors will assess \( H \) units of projects,
whereas $H = \sum_{i}^{N} h_i$. Since all sophisticated investors are identical, we can simplify $H$ as $H = Nh$, whereas each sophisticated investor would do $h$ unit of valuation and aggregately $H$ unit of projects are assessed.

We further assume the sophisticated investors do their valuations in two subsequent periods. Each sophisticated investor assesses $\frac{h}{2}$ unit of projects each in both periods. Projects being assessed by sophisticated investor $i$ in period $t$ are randomly drawn from the total remaining unsold projects excluding all projects by valued sophisticated investor $i$, whereas $i \in \{1, \ldots, N\}$. For each period $t$, whereas $t \in \{1,2\}$, $\tilde{\lambda}_t$ proportion of valued projects are good projects. We denote the expected value of $\tilde{\lambda}_t$ as $\lambda_t = E[\tilde{\lambda}_t]$. Figure A1 illustrates the valuation process in sophisticated market for period $t$, whereas $t \in \{1,2\}$.

For period 1, the expected portion of good assets that being evaluated should equal to the portion of good assets in the unit mass, i.e. $\tilde{\lambda}_1 = \lambda$. For period 2, bad project whom are identified by one sophisticated investor in period 1 have motivation to approach another sophisticated investor and get valued again. There are two drivers for this behaviour. First, valuation is non-verifiable. When a bad project seller’s identity is known to sophisticated investor $i$, it will remain unknown to all other sophisticated investors $j$ if no information sharing. Therefore, the bad project seller can approach another sophisticated investor and pretend to be the sellers haven’t been valued in period 1. Second, since the valuation is noisy, the bad projects have a probability of $\varepsilon$ being valued as good projects and being sold at $P^S$. This creates incentive for those bad projects which are identified in period 1 to get another valuation in period 2.
**Hypothesis 1**: Without information sharing, in period 2, the fraction of the good projects being valued is smaller than the fraction of the good projects in the overall population. i.e. \( \lambda_2 < \lambda \).

Intuitively, in period 2, we have a higher bad project ratio than period 1 since all projects being rejected in period 1 will reenter the valuation pool. Most of them are bad projects, given the period 1 valuation is relatively accurate (i.e. valuation noise \( \varepsilon \) is small enough). Therefore, we can get \( \lambda_2 < \lambda \). This makes sophisticated investors’ valuation less efficient since they are getting a smaller fraction of good projects than overall population fraction. And this inefficiency is due to the fact that valued bad projects dilute information acquisition procedure.

**Information sharing**

To mitigate such inefficiency from information dilution, sophisticated investors can share information about the bad projects that is identified in period 1 to each other. Formally, we denote each sophisticated investor reveals \( \theta \) fraction of the bad projects’ identities to her peers, whereas \( \theta \in [0,1] \). Since information sharing prevent bad projects from period 1 diluting information acquisition, it will increase the fraction of good projects being valued in period 2.

**Hypothesis 2**: With information sharing, the fraction of the good projects being valued in period 2 increases with regard to the level of information sharing, i.e. \( \lambda_2 \) increases with regard to \( \theta \).

The pricing mechanism and market clearing conditions will be identical to the main result and all previous result will sustain. The only difference is the pricing changes under noisy valuation, and it’s illustrated in C.3.

C.1 Proof of Hypothesis 1

For period 1, each sophisticated investor values \( \frac{n}{2} \) unit of projects. Among them, \( \lambda_1 = \lambda \) of them are good projects and \( 1 - \lambda \) of them are bad projects. In total, each sophisticated investor identifies \( \frac{n}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] \) unit of projects as good projects and buys them.
Among them, \( \frac{h}{2} \cdot \lambda \cdot (1 - \varepsilon) \) are good projects and \( \frac{h}{2} \cdot (1 - \lambda) \cdot \varepsilon \) are bad projects. On the other hand, each sophisticated investor identifies \( \frac{h}{2} \cdot [\lambda \cdot \varepsilon + (1 - \lambda) \cdot (1 - \varepsilon)] \) unit of projects as bad projects and rejects them. In aggregate, \( N \cdot \frac{h}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] = \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] \) unit of goods are bought.

In period 2, for sophisticated investor \( i \), her expected valuation pool will be \( V_i^2 = 1 - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] - \frac{h}{2} \cdot \lambda \cdot \varepsilon \). The first term represents the expected fraction of unsold projects in period 2. The second term represents the expected fraction of projects which are rejected by sophisticated investor \( i \) in period 1. Among those projects, there are \( G_i^2 = \lambda - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon)] - \frac{h}{2} \cdot \lambda \cdot \varepsilon \) units of expected good projects. The first term represents the expected total remaining unsold good projects in period 2. The second term represents the expected fraction of good projects which are rejected by sophisticated investor \( i \) in period 1. Therefore, we can get the expected proportion \( \lambda_2 \) of good projects in period 2 as following:

\[
\lambda_2 = \frac{G_i^2}{V_i^2} = \frac{\lambda - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon)] - \frac{h}{2} \cdot \lambda \cdot \varepsilon}{1 - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] - \frac{h}{2} \cdot \lambda \cdot \varepsilon - \frac{H}{2} \cdot (1 - \varepsilon)}
\]

Then, \( \lambda_2 < \lambda \) is equivalent to

\[
\frac{\lambda - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon)] - \frac{h}{2} \cdot \lambda \cdot \varepsilon}{1 - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] - \frac{h}{2} \cdot \lambda \cdot \varepsilon - \frac{H}{2} \cdot (1 - \varepsilon)} < \lambda
\]

Simplify [15], we can get

\[
\lambda - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon)] - \frac{h}{2} \cdot \lambda \cdot \varepsilon < \lambda - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] - \frac{h}{2} \cdot \lambda - \frac{H}{2} \cdot (1 - \varepsilon) - \frac{h}{2} \cdot \varepsilon < -\frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] - \frac{h}{2} \cdot [\lambda \cdot \varepsilon + (1 - \lambda) \cdot (1 - \varepsilon)]
\]
\[
\frac{H}{2} \left[ \lambda \ast (1 - \varepsilon) + (1 - \lambda) \ast \varepsilon \right] - \frac{H}{2} \left( 1 - \varepsilon \right) < \frac{h}{2} \ast \varepsilon - \frac{h}{2} \ast \left[ \lambda \ast \varepsilon + (1 - \lambda) \ast (1 - \varepsilon) \right]
\]

\[
\frac{H}{2} \left[ (\lambda - 1) \ast (1 - \varepsilon) + (1 - \lambda) \ast \varepsilon \right] < \frac{h}{2} \ast (1 - \lambda) \varepsilon - \frac{h}{2} \ast (1 - \lambda) \ast (1 - \varepsilon)
\]

\[
N \ast (1 - \lambda) \ast (2\varepsilon - 1) < (1 - \lambda) \ast (2\varepsilon - 1)
\]

Given \( N > 1 \), \( \varepsilon < \frac{1}{2} \) and \( \lambda \in (0,1) \), we can show [16] is true.

C.2: Proof of Hypothesis 2

With information sharing, period 1 valuation procedure is unaffected since there is no information to share yet. In period 2, each sophisticated investor reveals \( \theta \) fraction of the bad projects’ identities to her peers, whereas \( \theta \in [0,1] \). One can consider \( \theta \) as a modification for \( \sigma \) in the main model. In the main model we illustrate information sharing \( \sigma \) as how difficult bad projects to approach multiple sophisticated investors. Here \( \theta \) represents how much information each sophisticated investor share to other sophisticated investors. For sophisticated investor \( i \), her expected valuation pool will be

\[
V_i^2 = 1 - \frac{H}{2} \ast \left[ \lambda \ast (1 - \varepsilon) + (1 - \lambda) \ast \varepsilon \right] - \left[ 1 + (N - 1) \ast \theta \right] \ast \frac{h}{2} \ast \left[ \lambda \ast \varepsilon + (1 - \lambda) \ast (1 - \varepsilon) \right]
\]

The first term represents the expected total remaining unsold projects in period 2. The second team represents the expected fraction of projects which are rejected by sophisticated investor \( i \) in period 1 and the rejected projects revealed by other sophisticated investors. Among those projects, there are

\[
G_i^2 = \lambda - \frac{H}{2} \ast \left[ \lambda \ast (1 - \varepsilon) \right] - \left[ 1 + (N - 1) \ast \theta \right] \ast \frac{h}{2} \ast \lambda \ast \varepsilon
\]

units of expected good projects. The first term represents the expected total remaining unsold good projects in period 2. The second team represents the expected fraction of good projects which are rejected by sophisticated investor \( i \) in period 1 and the rejected good projects revealed by other sophisticated investors. Therefore, we can get the expected proportion \( \lambda_2 \) of good projects in period 2 as following:

\[
[17] \quad \lambda_2 = \frac{G_i^2}{V_i^2} = \frac{\lambda - \frac{H}{2} \ast \lambda \ast (1 - \varepsilon) - 1 + (N - 1) \ast \theta \ast \frac{h}{2} \ast \lambda \ast \varepsilon}{1 - \frac{H}{2} \ast \left[ \lambda \ast (1 - \varepsilon) + (1 - \lambda) \ast \varepsilon \right] - \left[ 1 + (N - 1) \ast \theta \right] \ast \frac{h}{2} \ast [\lambda \ast \varepsilon + (1 - \lambda) \ast (1 - \varepsilon)]}
\]

We still can show \( \lambda_2 < \lambda \) as long as \( \theta < 1 \).

Simplify [17], we can get
Given $N > 1$, $\theta < 1$, $\varepsilon < \frac{1}{2}$ and $\lambda \in (0,1)$, we can show the above inequality is true.

Next, we need to show $\lambda_2$ increases with regard to $\theta$, given that

$$\lambda_2 = \frac{G_i^2}{V_i^2} = \frac{\lambda - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon)] - [1 + (N - 1) \cdot \theta] \cdot \frac{h}{2} \cdot \lambda \cdot \varepsilon}{1 - \frac{H}{2} \cdot [\lambda \cdot (1 - \varepsilon) + (1 - \lambda) \cdot \varepsilon] - [1 + (N - 1) \cdot \theta] \cdot \frac{h}{2} \cdot [\lambda \cdot \varepsilon + (1 - \lambda) \cdot (1 - \varepsilon)]}$$

Taking derivative of $\lambda_2$ with regard to $\theta$, we can show
\[
\frac{d\lambda_2}{d\theta} = \frac{(N - 1) \frac{h}{2} \lambda (1 - \lambda) (1 - 2\varepsilon) (1 - H \lambda) \left[ 1 + (N - 1) \theta \right] \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon)}{\left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right)^2} > 0
\]

\[
\frac{d\lambda_2}{d\theta} = \frac{-\varepsilon \left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right) \left[ 1 + (N - 1) \theta \right] \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon)}{\left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right)^2}
\]

Take out common factor of \((N - 1) \frac{h}{2} \lambda\) at the top.

\[
\frac{d\lambda_2}{d\theta} \propto \frac{-\varepsilon \left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right) \left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right)}{\left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right)^2}
\]

\[
A = \lambda \varepsilon (1 - \lambda) (1 - \varepsilon), \text{ then } 1 - A = \lambda \varepsilon (1 - \varepsilon) + (1 - \lambda) (1 - \varepsilon)
\]

\[
\frac{d\lambda_2}{d\theta} \propto \frac{-\varepsilon \left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right) \left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right)}{\left( 1 - \frac{H}{2} \lambda (1 - \varepsilon) (1 - \lambda) - \left( 1 + (N - 1) \theta \right) \frac{h}{2} \lambda (1 - \lambda) (1 - \varepsilon) \right)^2}
\]
\[ \frac{d \lambda_2}{d \theta} \]
\[ \alpha \frac{-\varepsilon + \frac{H}{2} \varepsilon - \frac{H}{2} \varepsilon A + A - \frac{H}{2} A + \frac{H}{2} A \varepsilon}{\left\{1 - \frac{H}{2} [\lambda (1 - \varepsilon) + (1 - \lambda) \varepsilon] - \left[1 + (N - 1) \theta\right] \frac{h}{2} [\lambda \varepsilon + (1 - \lambda) (1 - \varepsilon)]\right\}^2} \]
\[ \frac{d \lambda_2}{d \theta} \]
\[ \alpha \frac{-\varepsilon + \frac{H}{2} \varepsilon + A - \frac{H}{2} A}{\left\{1 - \frac{H}{2} [\lambda (1 - \varepsilon) + (1 - \lambda) \varepsilon] - \left[1 + (N - 1) \theta\right] \frac{h}{2} [\lambda \varepsilon + (1 - \lambda) (1 - \varepsilon)]\right\}^2} \]
\[ \frac{d \lambda_2}{d \theta} \]
\[ \alpha \frac{(A - \varepsilon)(1 - \frac{H}{2})}{\left\{1 - \frac{H}{2} [\lambda (1 - \varepsilon) + (1 - \lambda) \varepsilon] - \left[1 + (N - 1) \theta\right] \frac{h}{2} [\lambda \varepsilon + (1 - \lambda) (1 - \varepsilon)]\right\}^2} \]
\[ \frac{d \lambda_2}{d \theta} \]
\[ \alpha \frac{(\lambda \varepsilon + (1 - \lambda) (1 - \varepsilon) - \varepsilon)(1 - \frac{H}{2})}{\left\{1 - \frac{H}{2} [\lambda (1 - \varepsilon) + (1 - \lambda) \varepsilon] - \left[1 + (N - 1) \theta\right] \frac{h}{2} [\lambda \varepsilon + (1 - \lambda) (1 - \varepsilon)]\right\}^2} \]
\[ \frac{d \lambda_2}{d \theta} \]
\[ \alpha \frac{(1 - \lambda) (1 - 2 \varepsilon)(1 - \frac{H}{2})}{\left\{1 - \frac{H}{2} [\lambda (1 - \varepsilon) + (1 - \lambda) \varepsilon] - \left[1 + (N - 1) \theta\right] \frac{h}{2} [\lambda \varepsilon + (1 - \lambda) (1 - \varepsilon)]\right\}^2} \]
\[ > 0 \]

C.3 Pricing in noisy valuation

First, we analysis the remaining projects after sophisticated investors’ valuation. In period

1, sophisticated investors identify \( \frac{H}{2} [\lambda_1 (1 - \varepsilon) + (1 - \lambda_1) \varepsilon] \) unit of projects as good projects and buys them. Among them, \( \frac{H}{2} [\lambda_1 (1 - \varepsilon)] \) unit of projects are good projects and \( \frac{H}{2} [(1 - \lambda_1) \varepsilon] \) unit of projects are bad projects. In period 2, sophisticated investors
identify $\frac{H}{2} \ast [\lambda_2 \ast (1 - \varepsilon) + (1 - \lambda_2) \ast \varepsilon]$ unit of projects as good projects and buys them.

Among them, $\frac{H}{2} \ast [\lambda_2 \ast (1 - \varepsilon)]$ unit of projects are good projects and $\frac{H}{2} \ast [(1 - \lambda_2) \ast \varepsilon]$ unit of projects are bad projects. Therefore, the size of good projects in the pooling market is $\lambda - \frac{H}{2} \ast [(\lambda_1 + \lambda_2) \ast (1 - \varepsilon)]$. The size of bad projects in the pooling market is $(1 - \lambda) - \frac{H}{2} \ast [(2 - \lambda_1 - \lambda_2) \ast \varepsilon].$

On the other hand, for sophisticated investors, $\frac{1}{2} \ast [(\lambda_1 + \lambda_2) \ast (1 - \varepsilon)]$ and $\frac{1}{2} \ast [(2 - \lambda_1 - \lambda_2) \ast \varepsilon].$
3.9 Tables and Figures
Table 10: Features of four equilibria

<table>
<thead>
<tr>
<th>Unsophisticated investors’ trading constraint: $P^u(H) &gt; 1$ or $P^u(H) \leq 1$</th>
<th>Unsophisticated trade in pool</th>
<th>Unsophisticated don’t trade in pool</th>
</tr>
</thead>
</table>
| Sophisticated investors’ profit constraint: $E_i(\pi^S(p^u(H))) > 0$  
Or $E_i(\pi^S(p^u(H))) \leq 0$ | Valuation | Mixed equilibrium |
| Valuation | Mixed equilibrium | Pure valuation equilibrium |
| No valuation | Pooling equilibrium | No-trade equilibrium |
Table 11: Cost constraints and market quality constraints of four equilibriums

<table>
<thead>
<tr>
<th>Equilibriums</th>
<th>Cost constraint: ( c )</th>
<th>Market quality constraint: ( \lambda )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooling equilibrium</td>
<td>( c \geq \frac{\lambda^* (1 - \lambda) (R^g - R^b)}{R} )</td>
<td>( \lambda &gt; \frac{R - R^b}{R^g - R^b} )</td>
</tr>
<tr>
<td>No-trade equilibrium</td>
<td>( c \geq \frac{\lambda^* (R^g - R^b)}{R} )</td>
<td>( \lambda \leq \frac{R - R^b}{R^g - R^b} )</td>
</tr>
<tr>
<td>Pure valuation</td>
<td>( c &lt; \frac{\lambda^* (R^g - R^b)}{R} )</td>
<td>( \lambda \leq \frac{\lambda - \lambda^* \overline{H}}{1 - \lambda^* \overline{H}} \leq \frac{R - R^b}{R^g - R^b} )</td>
</tr>
<tr>
<td>equilibrium</td>
<td></td>
<td>( \lambda &gt; \frac{\lambda - \lambda^* \overline{H}}{1 - \lambda^* \overline{H}} ) &gt; \frac{R - R^b}{R^g - R^b}</td>
</tr>
<tr>
<td>Mixed equilibrium</td>
<td>( c &lt; \frac{\lambda^* (1 - \lambda) (R^g - R^b)}{(1 - \lambda^* H)R} )</td>
<td></td>
</tr>
</tbody>
</table>
Figure 7: Equilibria regions in quality-cost ($\lambda, c$) plane
Figure 8: Welfare changes comparing a partial information sharing regime and a complete information sharing regime

Pooling equilibrium changes to pure valuation equilibrium and social welfare decreases.

Pooling equilibrium changes to mixed equilibrium and social welfare increases.

Full information sharing VS Incomplete information sharing
Figure 9: Valuation, sophisticated investors' profits and social welfare in pure valuation/pooling region
Figure 10: Increasing information sharing in pure valuation/pooling region
Figure 11: Valuation, sophisticated investors' profits and social welfare in mixed/pooling region
Figure 12: Increasing information sharing in mixed/pooling region
Figure 13: Changes in minimum shock required and social welfare drop with regard to information sharing level
Figure 14: Expected drop in welfare with regard to information sharing in different business cycles

Expected drop V.S. information sharing

- **Recession**
- **Boom**

Expected drop level: $\sigma$

<table>
<thead>
<tr>
<th>Expected drop</th>
<th>Information sharing level: $\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.012</td>
<td>0</td>
</tr>
<tr>
<td>0.010</td>
<td>0.1</td>
</tr>
<tr>
<td>0.008</td>
<td>0.2</td>
</tr>
<tr>
<td>0.006</td>
<td>0.3</td>
</tr>
<tr>
<td>0.004</td>
<td>0.4</td>
</tr>
<tr>
<td>0.002</td>
<td>0.5</td>
</tr>
<tr>
<td>0.002</td>
<td>0.6</td>
</tr>
<tr>
<td>0.002</td>
<td>0.7</td>
</tr>
<tr>
<td>0.002</td>
<td>0.8</td>
</tr>
<tr>
<td>0.002</td>
<td>0.9</td>
</tr>
<tr>
<td>0.002</td>
<td>1.0</td>
</tr>
</tbody>
</table>
Figure A1: Noisy valuation

Valuation

$\lambda_t$

Good assets

1-$\epsilon$

Sold

$\epsilon$

Unsold

1-$\lambda_t$

Bad assets

$\epsilon$

Sold

$1-\epsilon$

Unsold