THREE ESSAYS IN FINANCIAL MARKETS AND BANKING

BY

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DISSERTATION

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Abstract

My first essay, *Domestic, Nonfinancial Commercial Paper after 2000*, examines why the commercial paper (CP) outstanding of domestic nonfinancial firms plunge in early 2000's and never recover. By looking at the past 21 years from January 1993 to December 2013, with a sample including all domestic, non-financial, non-utility firms that have CP ratings from Moody's, I find two main results. First, I find that firms' financing needs have been decreasing at the aggregate level since 2000. Additionally, although there have been constant new entrants, a big decline in CP market entry largely due to the credit deterioration of U.S. corporations since 2000, coupled with a high CP market exit rate largely due to a significant credit deterioration in the CP market itself has led to a large decline in CP issuers. With the average firm's CP issuance generally stable, the entire CP outstanding has remained at a low level. Among all firms, P-1 rated firms appear to contribute the most to the decrease of CP outstanding. An examination of the industry composition also provides evidence that firms from some industries that used to participate in CP market has now stopped accessing the market. Secondly, when a firm with a prime rating (P-1/P-2) expect a credit downgrade, has a lower M/B ratio, is a relatively small firm, has decreased investment opportunities, inventory or sales growth, and has increased cash holding or tangibility, it is more likely to exit the CP market. Upon exiting, it is likely to resort to its cash holding, private placement bonds or acquisition notes. For a firm with a non-prime rating upon exiting, it is likely to make changes in many areas of its debt structures. Finally, evidence is found that for firms exiting the CP market, the cost of their drawn down loan commitment is significantly increased.

The second essay, *China's Delisting Rule and Its Impact on Listed Companies*, studies whether Chinese loss firms take earnings management measures to improve their accounting performance after China's 1998 accounting-based regulation on firm delisting. I use the delisting rule as identification strategy and apply Regression Discontinuity Design (RDD) to examine whether loss reversed firms resort to accrual manipulation, real activity manipulation or other methods of earnings management in order to reverse their loss. My result consistently shows that firms that are just able to reverse loss in the third year use less non-operating net income and this result is mainly driven by firms that have the least amount of loss in the second year.

The third essay, *Soft Information and Internal Credit Ratings of Bank Loans*, answers whether soft information plays an important role in a bank's internal credit ratings and if it does, whether it leads to a "better" or "worse" prediction of the borrowing firm's future financial health through an empirical study in the Chinese banking industry. Understanding how banks' internal ratings work is important both for us to understand banks' lending and corporations' financing behavior, and for assisting banks' transition to more complicated risk management system and assisting bank regulators for their bank regulations decisions. Results from this research show that soft information indeed affects internal ratings. Furthermore, soft information contributes positively to a bank's prediction of a firm's loan performance and future financial health. This paper contributes to the literature by examining the evolution of internal ratings and by relating internal ratings to the real outcomes of loans.

To my husband Bill, my children David, Lisa, and Kaleb,

my father Huicai, and mother Renling,

with all my love and gratitude

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Chapter 1

Domestic, Nonfinancial Commercial Paper after 2000

1.1 Introduction

Commercial Paper (CP) market in the U.S. is a large and important debt market which before 2008 accounted for the largest proportion of money market mutual fund (MMMF) assets (see Figure 1.1). At the end of 2012 $1 trillion in CP was outstanding and is 6.5% of GDP in that year[1]. In the fourth quarter of 2012, daily placements of CP averaged about $58.53 billion, principally in maturities of 90 days or less, and each day an average of about 1,933 firms issued new paper[2]. The CP market for domestic non-financial firms is one of the major sources of short-term public financing and liquidity for large U.S. corporations and accounts for about 10% of all paper outstanding (see Table 1.1 for the composition of CP market).

Domestic Non-Financial Commercial Paper (DNFCP) had enjoyed a steady growth from 1945 to 2000. Then in November 2000, right before the 2001 Recession[3], the level of outstanding CP plunged (see Figure 1.2). By September 2002, the DNFCP market had shrunk by more than 50% in its annual outstanding level! From then on, the DNFCP outstanding has been fluctuating around the low level and has never recovered. Using the annual GDP as a benchmark, DNFCP outstanding vs. GDP in my sample increased from 0.415% to 1.61% from 1991 to 2000, but then dropped to 0.483% in 2003 following 2001 recession, and then again to 0.306% in 2009 following the financial crisis. Looking at the past 21 years from January 1993 to December 2013, with a sample including all domestic nonfinancial firms that have CP ratings from

[1] See https://research.stlouisfed.org/fred2 for data on real GDP and CP outstanding. GDP for 2012 is 15,354.6 billion dollars (in Chained 2009 Dollars) and CP outstanding in 2012 is 992.8 billion dollars.
[2] See http://www.federalreserve.gov/releases/cp/volumestats.htm for data whose source is supplied by The Depository Trust and Clearing Corporation, http://www.federalreserve.gov/datadownload.
[3] 2001 recession is from March 2001- November 2001 as defined by the Business Cycle Dating Committee of the National Bureau of Economic Research. It lasted 8 months which is slightly less than average for recessions since World War II. November 2001 is the beginning of an expansion.

Moody's, I answer the following question: why did the CP outstanding of domestic nonfinancial firms plunge in the early 2000's and never recover?

The current CP literature has carefully examined the cyclicality of the CP market. One strand of paper show that aggregate CP issuance is countercyclical, and CP issuance rises during downturns to compensate for reduced bank financing (e.g., Kashyap, Stein, and Wilcox 1993, Gao and Yun 2013). While Calomiris, Himmelberg, and Wachtel (1995) challenges this view and suggests that CP issuance is pro-cyclical at the firm level since it is positively correlated with sales and earnings.

The existing CP literature has also contributed to the knowledge of the use of CP and firm-level characteristics of CP issuers. Evidence is found that CP is strongly correlated with increases in accounts receivable and despite its short maturity, CP is used to finance long-term projects. Specifically, CP is used for financing inventories and capital expenditures, or as bridge financing for short-term debt, and is later refinanced with long-term debt to limit rollover risk or to minimize transaction costs (e.g., Calomiris et al. 1995, Kahl, Shivdasani, and Wang 2015). As shown in Calomiris et al. (1995), only firms with high credit quality can enter into the CP market. If we hold constant long-term credit quality, access to CP market also depends on a variety of firm characteristics, such as large size, high collateral levels, high earnings levels, low earnings variance, and large stocks of liquid assets.

The existing literature has generally looked at the commercial paper market as one continuous development through the years. While in this paper, I document that the CP market is drastically different after 2000 and examine the change and reason for the change that happened in the DNFCP market after 2000.

Other than CP literature, my paper is also related to the capital structure, especially debt structure literature. Collar, Ippolito and Li (2013) uses a sample of public U.S. firms from 2002-2009. They find that large rated firms simultaneously employ multiple types of debt; while all other firms, which comprise the majority of listed firms in the U.S., make use of only one type of debt. They also find that large, mature, profitable firms with more tangible assets, high leverage, and a credit rating use multiple sources; while firms with high growth opportunities, cash holdings, cash flow volatility, R&D expenses, and advertising expenses, and firms with unique products and a strong board, specialize in few types of debt. Rauh and Sufi (2010) uses a sample of 305 randomly selected nonfinancial rated public U.S. firms from1996-2006. They find that almost ¾ of their firm-year observations employ more than two types of different debt instruments; and that ¼ of the sample firms experience a significant change in debt composition. High credit firms (BBB and higher) use primarily two tiers of capital – equity and senior unsecured debt; while low credit quality firms (BB and lower) tend to use several tiers of debt. In this research, I examine the change in firms' debt structure after they exit the CP market from 2000 - 2013.

I have two main results. First, I explain why CP outstanding remains low since 2000. Firms' *financing needs* (i.e. total debt, total inventory, accounts receivable, capital expenditure) *have been decreasing* at the aggregate level since 2000. Additionally, although there have been constant new CP entrants, a big *decline in CP entry* largely due to the *credit deterioration of U.S. corporations* since 2000, coupled with *a high CP exit rate* largely due to a significant *credit deterioration in the CP market* itself has led to a combined effect of having more exits than entry in the CP market. Thus, with the large decline in CP issuers and the *average firm's CP issuance being generally stable*, the entire CP outstanding has remained at a low level. Although firms decrease in all rating category in the CP market, being the largest issuer along with having the largest decrease in firm number in the CP market, P-1 rated firms appear to have contributed the most to the decrease of CP outstanding. An examination of the industry composition of firms provide evidence that firms from some industries that used to participate in CP market now stop accessing the market.

My second finding explores the characteristics of those firms that would exit the CP voluntarily and the outcome for all exiting firms. For a firm with a prime rating (P-1/P-2), it is more likely to exit the CP market when it expects a credit downgrade, has a lower M/B ratio, is a relatively small firm, has decreased investment opportunities, inventory or sales growth, or has increased cash holding or tangibility. Upon exiting, it is likely to resort to its cash holding, private placement bonds or acquisition notes. In summary, when firms voluntarily exist the CP market, a small number of them might expect to do so because of a perceived future decline in credit worthiness. However, more seem to exit due to lack of need to be in CP market or having sufficient cash holdings. For a firm with a non-prime rating, it is likely to make changes in many areas of its debt structures upon exiting. Evidence is also found that for all firms exiting the CP market, the cost of their drawn down loan commitment is significantly increased. Therefore, it appears that firms resort to cash holding to replace CP borrowing rather than line of credit.

This paper contributes to the literature on CP market, debt structure, and corporate liquidity by examining CP borrowings, an important source of short-term funding for large firms, and its relationship with firms' other substitutes for short term funds, especially credit lines and cash holdings. This research improves our understanding of the behavior of DNFCP by examining firms' characteristics and firms' short-term financing decisions making; it also provides evidence and "food for thought" to policy-makers regarding regulatory and monetary decisions affecting banks, firms, the CP market, and MMMFs.

The rest of the paper is organized as follows. Section 2 provides details of the data sources, sample construction and summary statistics. Section 3 examines the factors that contribute to the drastic decline of DNFCP since 2000 at the aggregate and firm level. Section 4 concludes.

1.2 Sample Selection and Descriptive Statistics

1.2.1 Sample Construction

Since firms are not required to report their CP issuance, firm-level data on CP activity are not readily available to the public or for academic use[4]. Therefore, I have hand-collected 21 years of annual and quarterly outstanding CP rating and outstanding data from January 1993 to December 2013.

First, I compiled a comprehensive set of firm-level Moody's CP ratings from the inception of CP ratings in the early 1970s (with the first rating being on September 30, 1971) to the end of 2013 collected from Moody's website. Due to regulatory guidelines, Moody's has to post most (if not all) of their credit ratings online[5]. This assures the completeness of the Moody's credit ratings in my sample. CP has credit risk and most papers are rated by one or more nationally recognized statistical rating organizations (NRSRO), such as Moody's Investor Service (Moody's), Standard and Poor's (S&P), and Fitch Ratings. In this paper, I use one of the most extensively used ratings for CPs - Moody's CP ratings. Table 1.2 shows Moody's short-term ratings definition.

Second, I construct a sample of CP borrowing data by collecting all available annual or quarterly amounts of CP outstanding information from their 10-K / 10-Q electronic filings (for most firms, they became electronically available starting in 1992 or 1993). This results a comprehensive firm-level panel dataset of CP borrowings and Moody's CP ratings from early 1990s (with the earliest time being 1991) to the end of 2013. It was then matched to Compustat for firms' fundamentals and Dealscan for loan data and cost of revolvers. As shown in Figure 1.2, on average, my sample matches the Federal Reserve's published aggregate domestic nonfinancial CP outstanding at a 71% rate.

Following Acharya, Almeida, and Campello (2013), I drop firms that are utilities, financial firms or quasi-public firms. Specifically I exclude firms that are in the following SIC categories: 4899 < SIC < 5000 or 5999 < SIC < 7000 or SIC > 8999. I then drop the firm-years with a missing, negative or 0 firm total assets. The final sample includes 8,385 firm-years with 392 unique domestic nonfinancial firms from 1993 to 2013.

I combine three sources of information to determine when a firm enters or exits the CP market: Moody's rating start and end date, 10-K and 10-Q texts, and CP outstanding amounts. I define the date when a firm first obtains its CP rating or has its first non-zero CP outstanding, whichever comes first, as the date of its entry into the CP market. I define the date when a firm receives a "NP" (non-prime) or "WR"

[4] Capital IQ (CIQ) has collected CP outstanding data since early 2000's and I have compared my collected data with CIQ CP data whenever possible. However, for firms that have both international and domestic CP, CIQ normally collects the aggregate amount, while I need the domestic outstanding only. There are also other discrepancies between their data and mine (e.g. due to mismatch with the Compustat fiscal year).

[5] This is further confirmed by a long-time representative at Moody's Investor Service.

(withdraw) rating or when CP outstanding first becomes 0 for consecutive 2 years as the date of its exit from the CP market. I then double check by reading through 10-K or 10-Q for explicit indication of firm entering or exiting the CP market whenever available.

I notice that many firms have zero-valued observations for their year-end CP outstanding although they actually have issued CP during the year. There is also a clear seasonality pattern in the quarterly data of CP outstanding. Downing and Oliner (2007) also report a year-end phenomenon. They find that term premiums for CP often jump up at year-end. Similarly, I find a year-end reduction in CP outstanding. Based on Musto (1997), one explanation is that institutional investors have incentives to substitute Treasury bills and other safe instruments for CP at year end in order to present a less risky portfolio in their balance sheet. A second explanation is that some firms and individuals have an increased demands for cash holdings ahead of the year-end, as proposed by Griffiths and Winters (2005). A third possible reason is that some firms have larger cash flow coming in at year end (for example, firms in retail business), thus reducing the need for external financing. Because of this seasonality, I decide to only use annual CP outstanding data instead of the quarterly data. In order to mitigate the year-end zero CP problem when firms actually issue CP during the year, I use the average CP outstanding calculated from the quarterly data to replace the "misleading" zero outstanding amounts whenever they occur.

I further winsorize the variables at the upper 99% and lower 1% bound in order to remove outliers. Table 1.3 shows the summary statistics of all the key variables that are used in subsequent analysis.

In the next section, I explore the reasons that could have contributed to CP's downward trend.

1.3 Evidence from the CP Market

1.3.1 Aggregate level - demand side story

First, I examine this phenomenon at the aggregate level.

One explanation could be that general macroeconomic conditions have caused firms' general need for total debt to drop. Consequently, firms' need to borrow in CP market decreases. It has been identified by exiting literature (e.g. Calomiris et al. 1995) that CP is used for financing inventories and capital expenditures and it is also strongly correlated with increases in accounts receivable, all of which are correlated with general economic conditions. If this is true, we would expect that when economic conditions worsen, inventories, receivables and capital expenditures decline, and consequently, CP needs are reduced. Therefore, if we were to observe that firms' total debt, total inventories, accounts receivables and capital expenditures have been decreasing since 2001, we can contribute this as one reason for the decrease of aggregate CP outstanding.

As shown in Figure 1.3, this is exactly the case. Firms' total debt (scaled by total assets) is in an upward trend before 2001, reaches its highest level between 1998 and 2001, and then decreases dramatically right after 2001 and remains at a low level ever since. Firms' total inventory, total receivables, and capital expenditure (all scaled by total assets) have been in a downward trend since 1998. This indicates that the reduction in CP outstanding can be partially due to the reduction of firms' general needs of debt.

However, this is not the sole reason. Again as indicated in Figure 1.3, I also find that although CP used to contribute a big proportion to all of these four accounts, its percentage value invariably reaches its peak in 2000 and decreases dramatically afterwards and has been staying at a relatively low level ever since. The fact that the reduction of CP is not proportional to the reduction of the accounts it finances shows that firms must have resorted to other forms of debt to satisfy their financing needs. In another word, there must be some other factors that are at work to reduce the CP outstanding.

Naturally, my next question is what could be the other factors that lead to the decrease of firms' CP borrowings? This leads to the following analysis.

1.3.2 Aggregate level - supply side story

My first inquiry is: could the decline in outstanding CP be due to a drop in the number of CP issuing firms or to a reduction in each firm's average CP issuance? Figure 1.4 Panel A shows that the number of CP issuers has been steadily dropping since its peak of 223 firms in 2000 to only about half of that number (112 firms) in 2013. In contrast, based on Figure 4 Panel B, average CP issuance appears to bounce back fairly quickly right after the 2001 recession and the 2009 financial crisis. Apparently, the decrease in CP outstanding is due to a decline in the number of CP issuers rather than a reduction in the amount each issuer is borrowing from the CP market.

What has caused the reduction in the number of CP issuers then? To answer this, I first examine the composition of CP issuers and seek to answer the following question: is it mainly a gradual exodus of existing issuers which caused the CP to shrink, potentially indicating a "dying" market? Or is CP still a viable market that has a mix of new and old issuers? Figure 1.5 shows that the CP market continues to have a significant number of new entrants. However, while from 1994 to 2000, there are more entries than exits into the CP market, starting from 2000, the opposite is generally true. This has led to the combined effect of a net decline in the total number of CP issuers after 2000 although more than 90% of the CP issuers each year are retained from the previous year. Apparently, CP market is still a viable market with constant new entrants.

However, why are there fewer entries and more exits? For the former, is it because there is a general deterioration in firms' credit ratings so that fewer reputable firms are available to enter the market? To check this, I examine the universe of all Compustat Non-financial firms that have an S&P long-term firm rating. The reason to do so stems from a high correlation of firms' long-term rating with their CP ratings, a fact documented in Moody's (2004). According to Moody's Investor Service report on short-term ratings methodology on October 24, 2012 (Moody's 2004), "Moody's short-term ratings are opinions on the relative likelihood of timely payment on short-term financial obligations, including commercial paper." "The key determinant for assigning a short-term rating to an issuer is that issuer's long-term risk of default." Consequently, "an issuer's short-term rating is normally derived from its long-term rating." The close relationship between the credit risk of long-term and short-term debt of the same issuer lead to a somewhat intentionally mechanical mapping between long-term rating and short-term rating. For example, A2 and above long-term ratings almost always get mapped to P-1; A3 to Baa2 get mapped to P-2. Non-matching do happen in practice, but it is rare and tends to last for a short period of time. There is also a close mapping relationship between the long-term (or short-term) ratings among different rating agencies. The mapping of long-term and short-term ratings between Moody's and S&P standards as depicted in Figure 1.6 reflects exactly this.

Since high credit quality is a requirement for entry into the CP market (Calomiris et al. 1995), I focus on examining only the highest quality firms in the Compustat universe. Figure 1.7 indicates that for the universe of Compustat's nonfinancial, non-utility firms, the number of firms with A ratings (defined as having one of "A", "A+", "A-", "AA", "AA+", "AA-", "AAA" S&P long-term firm ratings and corresponding to Moody's CP P-1 rating) increases from 1990 to 1998. However, since 2000, this number has been steadily decreasing. The percentage of A-rated firms among all Compustat's nonfinancial, non-utility firms has also gradually decreased from 35% in 1991 to 20% in 2000 and then to 13% in 2014. Since high credit quality is a necessary condition for entry into the CP market, the shortage in supply of high credit corporate issuers provides strong anecdotal evidence as to why there is a lower number of entrants into the CP market.

Similarly, in my sample on the CP market, I find evidence of firm credit deterioration. As shown in Figure 1.8, in general, firms with all ratings have enjoyed steady growth in the CP market before 2000. Although there is a decline in number for firms of all ratings after 2000, P-1 firms get the biggest hit and declines the fastest. The number of P-1 firms begins to decrease dramatically from 2000 to 2006 and then continues to stay at a low level. The percentage of P-1 firms in the CP market also steadily decreases from more than 50% in 1994 to barely 30% in 2006 and stays at a low level since then. On the other hand, P-3 and below rated firms have increased from around 15% in 2000 to around 25% between 2001 and 2013. With the increase of P-3 and non-prime rated firms in the CP market after 2000, more firms have to involuntarily exit the market. Additionally, after 2000, P-2 firms dominate the CP market in number.

MMMF has been the largest holder of CP. Based on SEC Rule 2a-7[6], MMMF are restricted to hold no more than 5% of their assets in tier-1 (e.g. P-1 rated) securities of any one issuer. This number drops to 0.5% when being applied to tier-2 (e.g. P-2 rated) securities of any single issuer and additionally MMMF can hold no more than 3% of the fund's total assets in total tier-2 securities. As can be seen, the restriction on holding tier-2 papers is much stricter than holding tier-1 papers in MMMF. Credit deterioration in the CP market, as exemplified by the increase of P-2 below firms and decrease of P-1 firms, thus increases the CP exit rates after 2000.

So far we have seen the effect of credit deterioration on the CP market entries and exits. The decreasing supply of prime grade firms from the Compustat universe appears to be a contributing factor to the low level of CP entry. The high percentage of P-2 and below firms in the CP market after 2000 could explain the high exit rates. The combined effect thus lead to a lower entry rate and higher exit rate in the CP market after 2000.

Further evidence in Figure 1.9 panel A shows that based on annual average issuance, other than being the highest rated firms, P-1 firms are also the largest CP issuers. Although the average issuance for both P-1 and P-2 firms drops from 2001-2003, starting in 2003, P-1 firms have continued to grow and become even bigger CP issuers than before 2000 and increase their average issuance between 2005 to 2013 to two to three times of its lowest level in 2003, while P-2 firms fluctuate at a relatively stable level and P-3 firms decrease in average issuance. However, since P-1 firms decrease greatly in number after 2000 (as shown above in Figure 1.8), the total annual issuance of P-1 firms have decreased since 2000 (as depicted in Figure 1.9 Panel B). P-2 and below firms also have a decline in total annual issuance due to the decline in number of firms. Thus the combined effect is decreased total CP outstanding.

I further explore if there has been any industry composition shift in the Compustat universe for the nonfinancial and non-utility firms or in the CP market that may help shed some light on the CP reduction. As shown in Figure 1.10, weighted by total assets for all Compustat firms, among the 8 non-financial and non-utility industries based on the first number of firms' SIC code, three have seen changes over the years. The largest non-financial industry - transportation, communications, electric, gas and sanitary services industry (SIC 4) has some minor decline in total assets since 2001 and correspondingly, a small change in firm number composition in the same period, too. For the other two much smaller industries, mining and construction industry (SIC 1) and manufacturing group 1 (SIC 2 – which includes food, tobacco, textile, apparel lumber, paper, chemical products and petroleum refining industries), the former has been growing in total assets with a relatively small growth in firm numbers, while the latter has seen a small decline in total assets with a stable firm number composition in the market. I notice that manufacturing group 2 (SIC

[6] Source: http://www.federalreserve.gov/releases/cp/about.htm.

3 - which includes leather, stone, metal products and telecommunication and transportation equipment) has kept a stable market share in total assets although its firm numbers have been declining greatly since 2000. As for the CP market, with result shown in Figure 1.11, we can see that for the two largest industries in the CP market - manufacturing group 1 (SIC 2) and manufacturing group 2 (SIC 3), while manufacturing group 2 (SIC3) firms have been relatively stable in both total assets (around 24%) and firm number compositions, manufacturing group 1 (SIC 2) has been growing rapidly in CP market share, from having similar market share with the manufacturing group 2 (SIC3) in 2000 (26% vs. 21%) to being 1.6 times of it in 2014 (42% vs. 26%) . Transportation, communications, electric, gas and sanitary services industry (SIC 4) have been declining drastically in total assets since 2000 with only a small decline in firm number composition. Its market share (based on total assets) dropped from 30% in 2000 to only 12% in 2014. There is a small decrease in both total assets and firm number composition for mining and construction industry (SIC 1).

With the total CP outstanding declining dramatically since 2000, if an industry has relatively stable or even increased market share in the Compustat universe, a stable or reduced CP market share of that industry would indicate a reduced firm participation from the particular industry. Based on the facts discussed in the previous paragraph, except for manufacturing group 1 (SIC 2)[7], all of the other three industries (SIC 1, SIC3 and SIC 4)[8] have shown evidence of lowered participation in the CP market. Let's take SIC 3 group of firms as an example. Shen (2003) listed examples of firms, such as Lucent Technologies, Nortel Networks, Motorola, in the telecommunication industry (with the first two SIC code being 36) that pulled out of the CP market because rating downgrade in the early 2001. This result provides another reason for the decline of DNFCP outstanding - firms that used to participate in CP market now turn away.

So far, evidence have been shown that both supply and demand factors have affected CP outstanding at the aggregate level since 2000. Next, I will start to look for firm level evidence for my question.

1.3.3 Firm level evidence – credit story or cost story?

In this section, I will explore why firms exit the CP market. For firms that are forced out the CP market due to a non-prime rating, I will examine what debt instruments they would resort to afterwards. For firms with prime credit, I will test whether they would exit the CP market voluntarily and if so, why. Is it because they can foresee a credit decline in the near future (the so called "credit story")? Is it because

[7] This group of firms have a small decrease in total assets in the Compustat universe but a big increase in CP market share.
[8] SIC 2 firms have an increase in total assets while a decrease CP market share; SIC 3 has stable total assets in both Compustat universe and the CP market; and SIC 4 firms have only minor decrease in the Compustat universe while big decrease in CP market share.

they have alternative financing measures to relieve their need of CP? Or is it because they have a low cost alternative (the so called "cost story")?

For the alternative financing means, I will focus my tests on revolvers and cash holdings. CP entails rollover risk. First of all, because of its short maturity, CP issuers generally issue new papers to retire the old ones, thus making it a rolling form of debt. The credit risk lies in that the issuer may not be able to issue new CP when the old papers come due. Most issuers obtain credit enhancements, such as line of credit (or revolver). Therefore, I suspect that firms may resort to revolvers if they exit the CP market - either when they are forced out of the market and need to pay off their old papers or when they voluntarily exit the market and are able to get a cheaper rate on the revolvers. Secondly, CP is usually used by companies to raise cash needed for current transactions. When there is enough cash holdings, I suspect that firms would choose to stop issuing the papers and turn to their cash holdings for current transaction needs since cash holdings are cheaper than CP under most circumstances.

I separate my sample into four groups as indicated in Table 1.4. I name the group of firms that stay in the CP market throughout my sample period with P-1 or P-2 ratings as Group 1; the group that exits the CP market with the last rating being P-1 or P-2 as Group 2; the group of firms that exit the CP market with last rating being P-3 or NP Group 3; and lastly, Group 4 for the very small number of firms that remain in the CP market with a non-prime credit rating (P-3 or NP). Although P-3 can be considered prime, firms normally cannot stay long after being downgraded to P-3. Thus, I consider it as a non-stable prime state and put it along with the other non-prime rating in Group 3 and 4. I suspect Group 4 firms will either have to improve their financial situation quickly or they will soon exit this market. Therefore, I will not examine Group 4 in this paper but rather focus my attention on comparing Group 1 and 2, and then Group 2 and 3. The summary statistics of key variables in each group are presented in Table 1.5.

I start out to explore the reasons for Group 1 and 2's different decisions. Given both firms having good credit rating and history of borrowing in the CP market, what leads them to decide whether to stay or exit the CP market? I am particularly interested in finding out why Group 2 exits the CP market. Is it because it expects its credit rating to deteriorate in the near future? Or is it because it has found a low cost alternative? Could this low cost alternative be the line of credit that is required when setting up the CP? Or is it because it has enough cash flow from its operation? Or maybe a combination of all of the above?

Figure 1.12 shows that for this combined primary rating group (Group 1 and Group 2 firms), Group 1 firms' proportion has been increasing over the sample period. This means conditional on having good ratings, more firms choose to stay in the CP market instead of exiting.

First, I want to examine whether these two groups of firms are fundamentally different. Table 1.6 Panel A compares Group 1 and Group 2 with all key variables normalized by total assets except size which is measure by log(total assets) or log(sales). As can be seen, the two groups are substantially different in many ways, and these differences are also statistically significant. On average, Group 1 are bigger firms, have a lower cost of borrowing via loan commitments, have more cash holdings and more operating cash flow, have less investment opportunities (measured by capital assets), have bigger inventory, have a faster sales growth, have lower leverage, have less tangible assets, have a bigger M/B, have more working capital, have more CP borrowings, have less free cash flows, have bigger accounts payable and receivables, and have a lower total debt.

Next, I explore whether Group 2 firms exit the CP market because they expect a rating downgrade in the near future. Here, I use the S&P long-term firm rating 1 to 3 years after Group 2 firms exit the CP market as my measure of firms' future credit. Grouping method of the S&P ratings is presented in Table 1.7 Panel D and mapping method of S&P long-term rating to Moody's CP rating again can be found in Figure 1.6.

Table 1.7 Panel A and C show that for P-1 firms, after 1 year, 65% firms still retain their P-1 ratings (corresponding to S&P firm rating 1) and this number drops to 54% in year 2 and year 3. For P-2 firms, 70% firms retain their primary rating (corresponding to S&P firm rating 1 and 2) after year 1 and this number remain relatively stable for the next two years. In summary, although some firms do get downgraded to a lower rating[9] after exiting the CP market, on average, around 54-70% of the firms retain their primary ratings (i.e. do not get downgraded) even after 3 years. This means, although there may be a small number of firms who expect a credit downgrade and thus exit accordingly, majority of the firms in Group 2 *voluntarily choose* to exit the CP market. Table 1.7 Panel B further shows that the average post-exit ratings for both last rating P-1 or P-2 firms are well within the prime rating range (≤ 2). It also provides evidence that CP ratings and S&P long-term firms ratings do correlate well.

Using the firm characteristics identified by existing literature (i.e. Calomiris et al. 1995) as important determinants for CP issuance, I further examine the factors that are important to a firm's exit decision by running a probit regression with the independent variables being those important firm characteristics and the dependent variable being one if a firm exits the CP market and zero otherwise. As shown in Table 1.8, when looking at the full sample, for a firm that has a prime credit rating (P-1 / P-2), it will be more likely to exit the CP market, if the following happens:

- If it expects its future credit to decrease;
- If it has a lower M/B ratio;
- If it is a relatively small firm;
- If its investment opportunity or inventory decreases (i.e. financing needs decrease);
- If its cash holding increases (i.e. alternative financing);

[9] Downgrading happens when P-1 firms gets S&P Firm Rating 2+; or when P-2 firms gets S&P Firm Rating 3+. S&P Firm Rating = 3, 4 is comparable to Moody's CP Rating = P-3, NP.

- If its bank commitments draw down is more expensive (which contradicts the cost story);
- If its tangibility is greater;
- Or if its sales slow.

When looking at the results based on the sample prior to and after the 2001 Recession, the main difference we see is that investment opportunities, inventory needs, and sales growth lose statistical significance in the post-2001 sample. In contrast, cash holdings, bank commitment draw downs, and leverage become important after 2001.

I then compare the key capital structure components as identified in the debt structure literature (e.g. Collar, Ippolito & Li 2013, Rauh and Sufi 2010) and aim to discover if there is any change before and after Group 2 firms' CP exit by using t-test on the pre-exit and post-exit paired samples. I have presented only the debt instruments that have shown statistically significant changes in Table 1.9 Panel A. It appears that after exit, Group 2 increases its 114A private placements of bond and acquisition notes, reduces its public bond issuance and shelf-registered debt. The percentage of public bond and shelf-registered debt compared to total debt also decreases. There is no significant change in its bank debt, either for bank term loans or bank revolvers.

Combining the results from Table 1.8 and 1.9, it appears that Group 2 firms are most likely exiting the CP market either for credit concerns, because there is a decline in their financing need, or because they have sufficient cash holdings. It is unlikely Group 2 firms are going to resort to loan commitments because of their high costs. I do not find evidence of Group 2 firms using other lower cost alternative financing means, either. It is likely that P-1 firms exit because there is increased cash holdings which alleviate their needs on CP issuance; while P-2 firms exit because either they foresee a credit decline in the near future or because they can resort to cash holdings to lower their costs since P-2 paper rates are much higher than P-1. Figure 1.13 also provides some anecdotal evidence that firms' cash holdings increase quickly after 2001 while CP level decreases when compared to cash holdings, indicating that cash holding could well be an alternative financing source for CP.

In the following section, I will explore the difference between the financing means of Group 2 and Group 3 firms after they exit the CP market.

I apply a similar t-test as to Group 2 on the pre-exit and post-exit paired samples for Group 3 firms. From Figure 1.14 Panel B, it can be seen that after 2001, firms that exit the market involuntarily (Groups 3) and those that do so voluntarily (Group 2) are comparable in number. However, as shown in Figure 1.9 Panel A, except for 2004 and 2005, on average, P-1 and P-2 firms issue more CP than P-3 firms. Thus, firms voluntarily exiting the CP (Group 2) appear to have a bigger effect on lowering the CP issuance than those exiting the CP market involuntarily (Group 3).

Furthermore, for Group 2, it may use CP temporarily followed by borrowing in the bond market. However, for Group 3 firms facing worse credit quality, they may have worsened access to the bond market. A notable example was in May 2005 when GM and Ford were downgraded to junk status, coinciding with a wide-spread sell-off of their corporate bonds. The question is how might Group 3 firms react once they are involuntarily out of the CP market? Would they resort to internal cash holdings or bank revolvers?

Table 1.9 Panel B shows that after exiting the CP market, Group 3 firms shift to more bonds, bank term loans, mortgage debt and equipment notes, and less medium term notes. Consequently, there appears to be a shift from short-term to long-term funding. Despite a decline in their commercial paper rating, these firms appear to remain sufficiently credit-worthy to access longer-term sources of financing.

1.4 Conclusion

The above analysis provides evidence for a credit-related, and both supply-side and demand-side channel explanation for the long-term decline in the DNFCP market.

First, at the aggregate level, there has been a big decline in firms' general financing needs (i.e. total debt, total inventory, accounts receivable, capital expenditure) since 2000. Additionally, although CP market is still viable with constant new entrants, on the one hand, a general downgrade of corporate credit since 2001 reduce the supply of CP issuers and raise the bar of CP market entry; on the other hand, credit deterioration in the CP market, exemplified by higher percentage of P-2 and below firms in the market after 2000, appears to have led to the high exit rates. Although higher-rated firms are more likely to maintain their CP programs after 2001, the combined effect of having more exits than entry in the CP market leads to the decline in CP issuers. Although on average, the CP issuance per firm does not change much since 2001, total CP outstanding decreased along with the number of issuers. With firm number decreasing in all rating category in the CP market, being the largest CP issuer along with having the largest decrease in firm number in the CP market, P-1 rated firms appear to have contributed the most to the decrease of CP outstanding. An examination of the industry composition of firms provide evidence that firms that used to participate in CP market now stop accessing the market.

Next, at the firm level, there is little evidence that firms voluntarily exit the CP to take advantage of lines of credit because my test shows that the costs of such borrowing is actually higher when firms exit. Rather, when firms voluntarily exist the CP market, a small number of them might expect to do so because of a perceived future decline in credit worthiness. However, more seem to exit due to lack of need to be in CP market or having sufficient cash holdings. It appears that P-1 firms exit because there is increased cash holdings and P-2 firms exit because they plan to resort to cash holdings as a cheaper source. While CP ratings are a significant factor in firms' decision to exit the CP market, it could also be due to significantly higher costs of CP participation when a firm's rating is lowered from P-1 to P-2.[10] .

I find that for a firms with a prime rating (P-1/P-2), it is more likely to exit the CP market when it expects a credit downgrade, has a lower M/B ratio, is a relatively small firm, has decreased investment opportunities, inventory or sales growth, and has increased cash holding or tangibility. Upon exiting, it is likely to resort to its cash holding, private placement bonds or acquisition notes. For a firm with a non-prime rating and has to leave the CP market involuntarily due to rating downgrade, upon exiting, it is likely to make changes in many areas of its debt structures. Even with a tainted credit, they appear to retain access to long-term sources of financing.

[10] For example, money market mutual funds, which are one of the largest purchases of commercial paper, have regulatory restrictions on the amount of P-2 rated paper that they can hold.

1.5 Tables and Figures

Figure 1.1 Money Market Mutual Fund (MMMF) portfolio holdings 1986 – 2012

This figure plots the time series of different account compositions in MMMF based on total assets. The source is http://www.federalreserve.gov/.

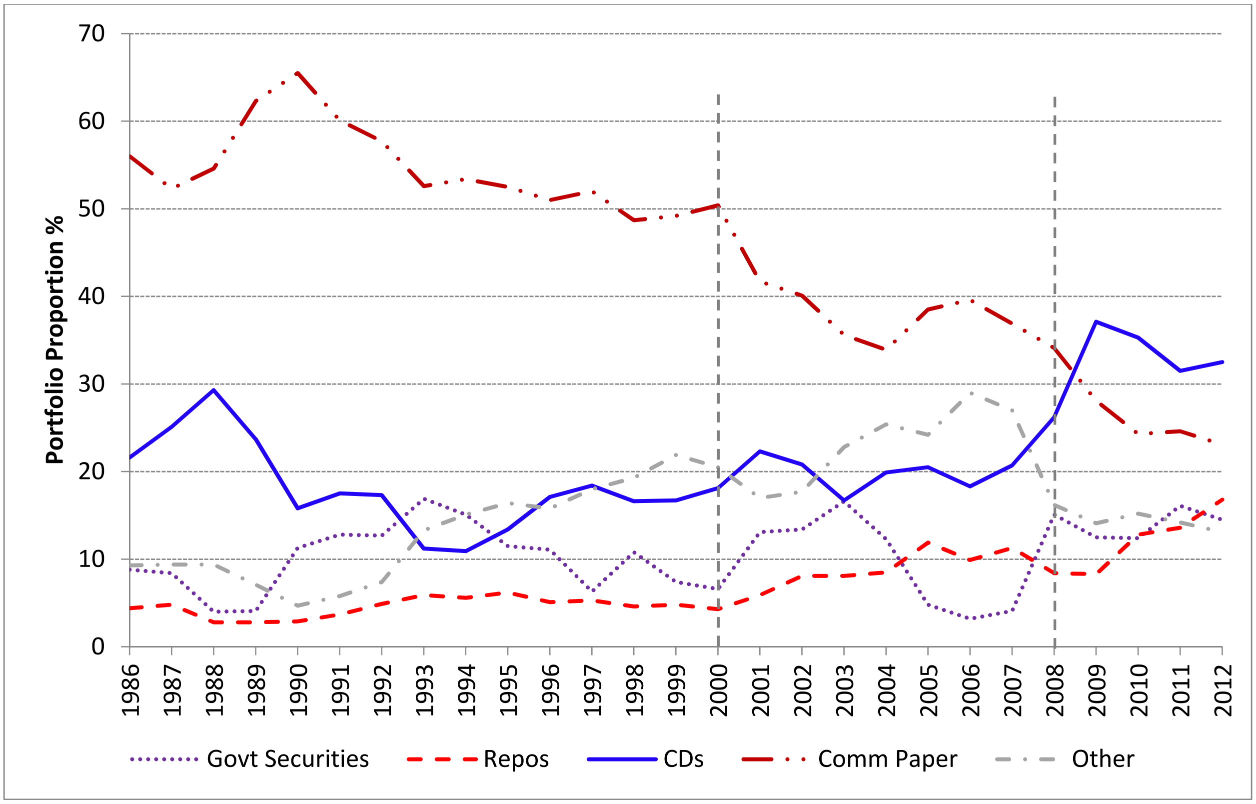


Figure 1.2 2013 End-of-year Domestic Nonfinancial CP Outstanding 1991-2013

This figure plots the time series of year-end CP outstanding from 1991 to 2013. It also compares my hand-collected sample data with the Federal Reserve's published data. On average, my sample matches the Fed's aggregate domestic nonfinancial CP outstanding at 71% rate.

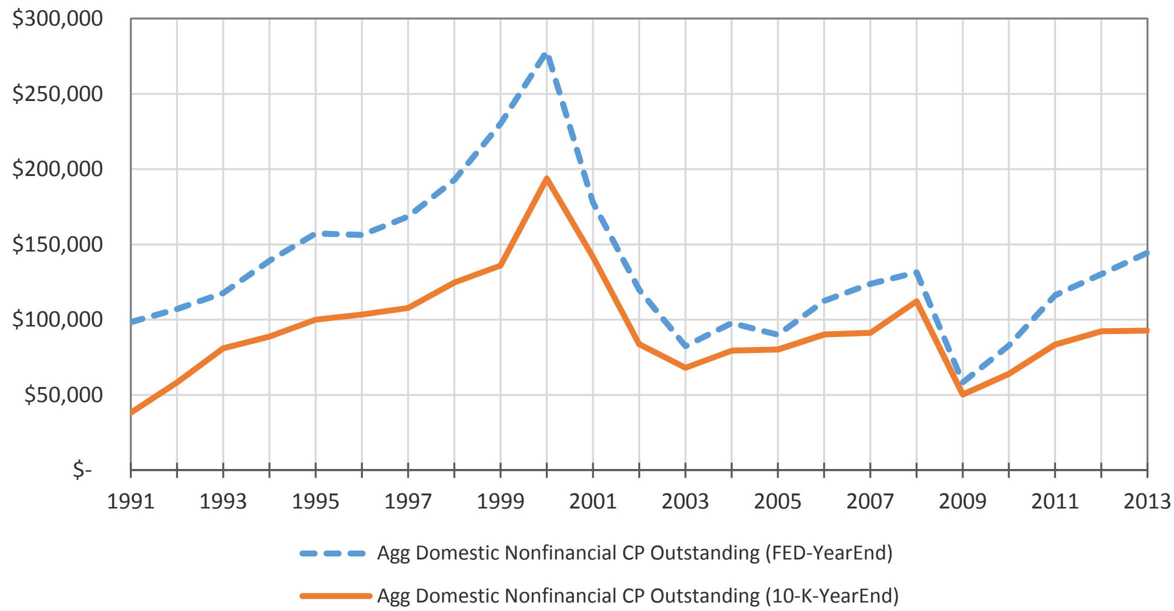


Figure 1.3 Sample firms' aggregate demand 1991-2013

This figure plots the time series of aggregate level of four accounts: total debt, total inventory, total receivable, and capital expenditures (all scaled by beginning of year total assets). For all four panels, the left axis represents the aggregate parameter (total debt, total inventory, total receivable, and capital expenditures) level (scaled by total assets), and the right axis represents the percentage composition of commercial paper (CP) compared to the respective parameter level.

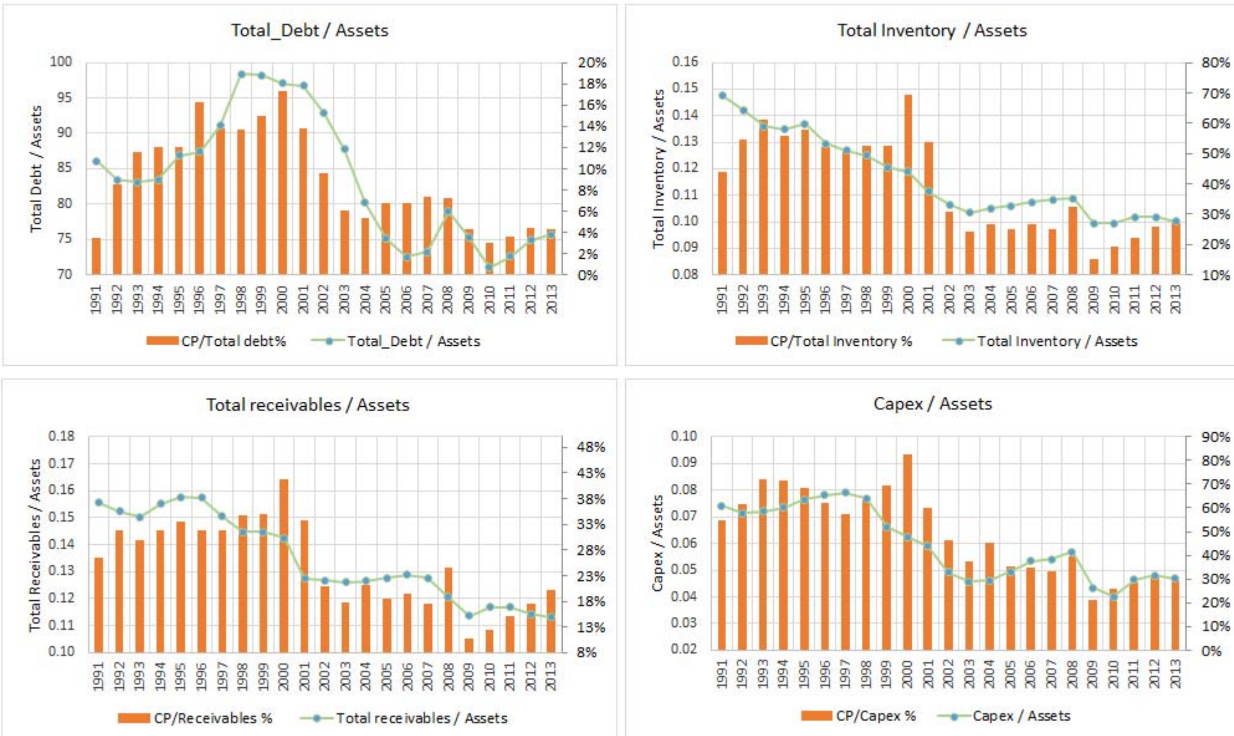
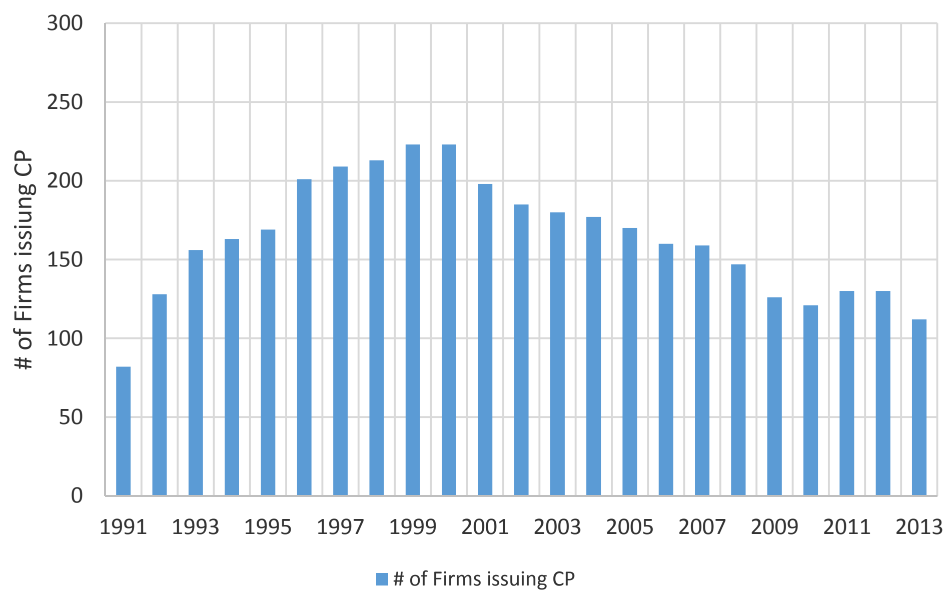


Figure 1.4 Number of DNFCP Issuers and Average CP Issuance 1991-2013

Panel A of this figure plots the time series of the number of DNFCP issuers from 1991-2013. Panel B of this figure plots the time series of DNFCP average annual issuance from 1991-2013.

Panel A: Number of CP Issuers 1991-2013



Panel B: Average CP Issuance 1991-2013

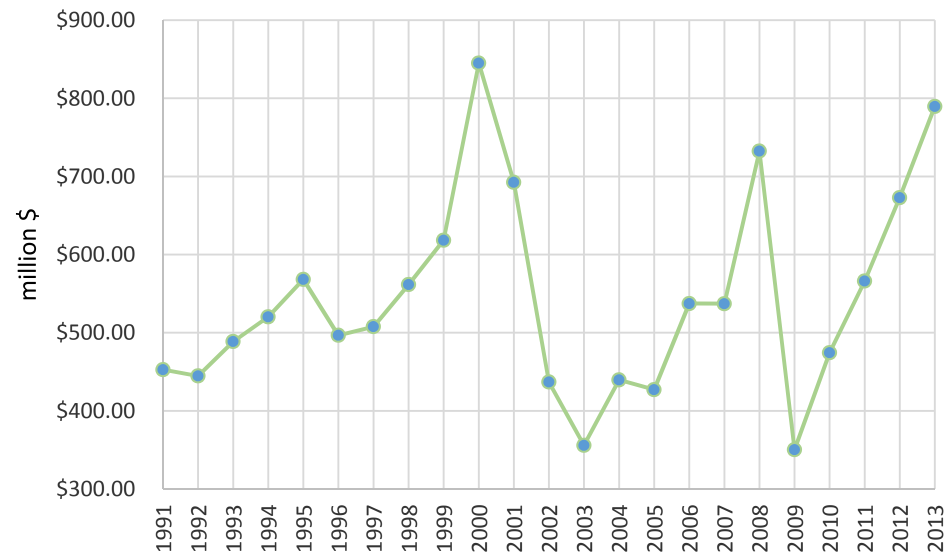


Figure 1.5 Percentage of DNFCP market firm entries and exits 1994-2013

This figure plots the time series of the annual DNFCP market number of entries and exits and the combined increase / decrease of the DNFCP market.

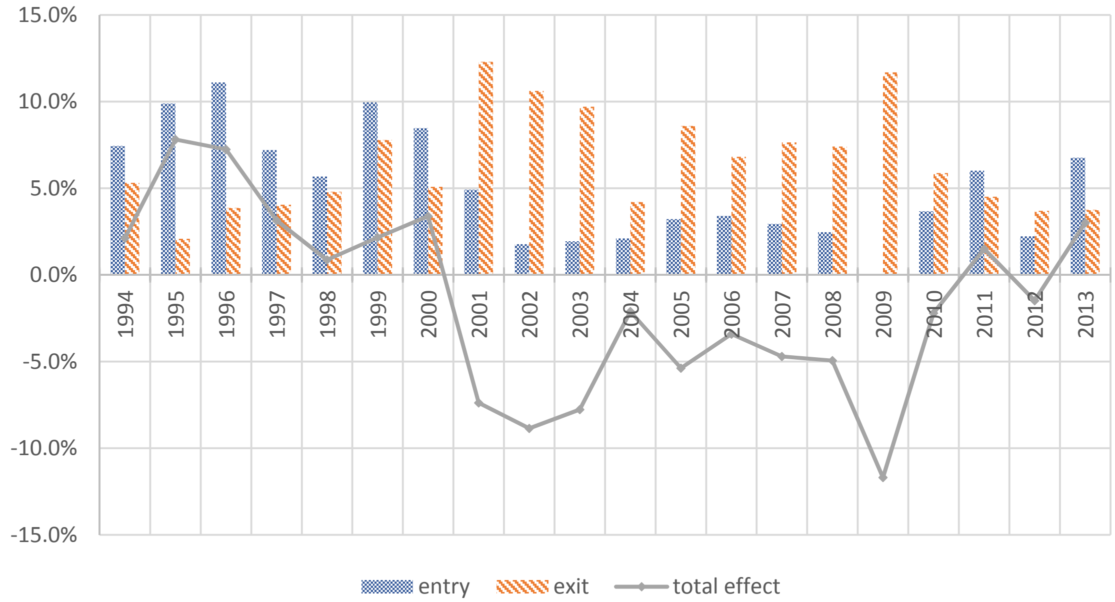


Figure 1.6 Mapping of Moody's and S&P Long-term and Short-term Ratings

This figure presents the mapping of the Moody's long-term and short-term, and S&P's long-term and short-term ratings.

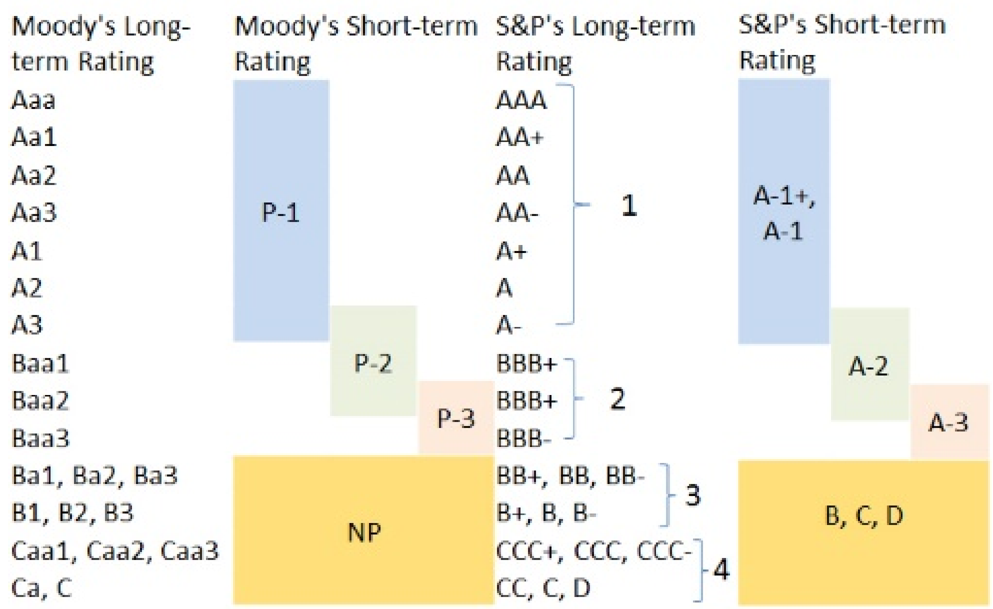


Figure 1.7 Compustat Non-financial Firms' S&P Long-term Credit Rating

This figure plots the time series of the number of firms and percentage of firms with S&P's long-term A rating. A ratings include "A", "A+", "A-", "AA", "AA+", "AA-", and "AAA". The left axis represents the number of A rated firms and the right axis represents the percentage of A rated firms among all firms.

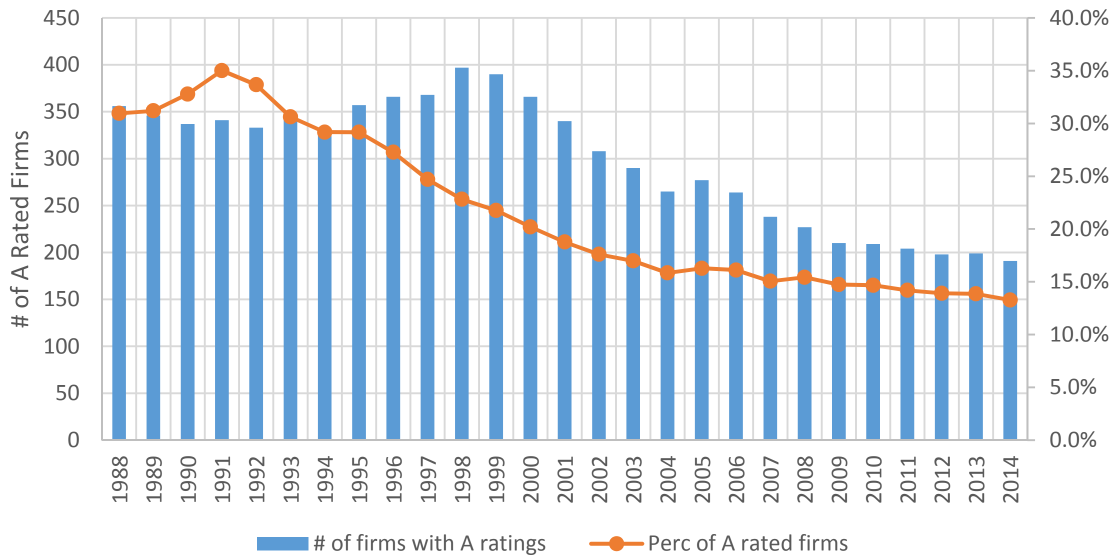
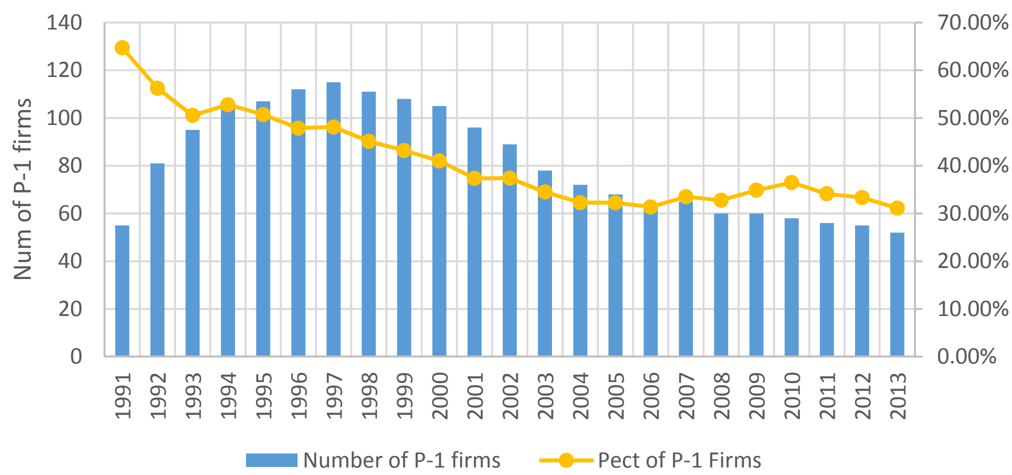


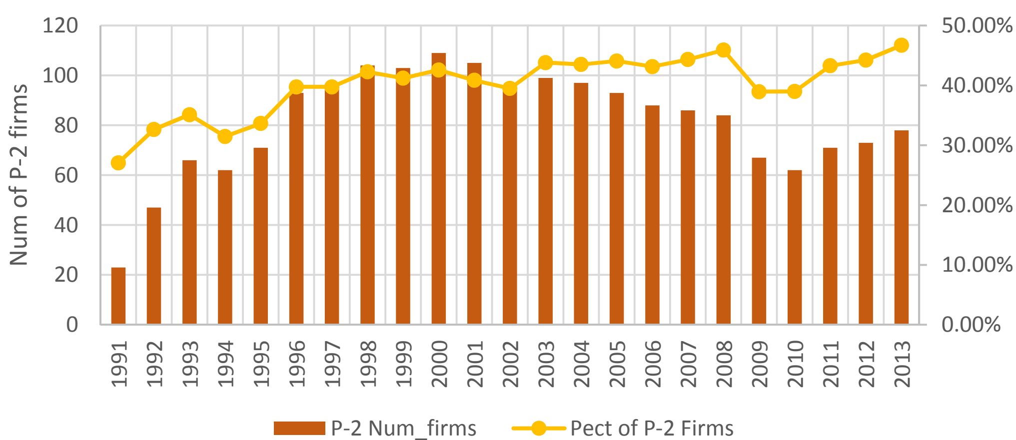
Figure 1.8 Commercial Paper Market Firms' Moody's CP Rating Composition 1991-2013

This figure plots the time series of the number and percentage of firms with different Moody's CP ratings. The left axis represents the number of firms and the right axis represents the percentage of firms.

Panel A: Number and percentage of P-1 firms



Panel B: Number and percentage of P-2 firms



Panel C: Number and percentage of P-3 and below rating firms

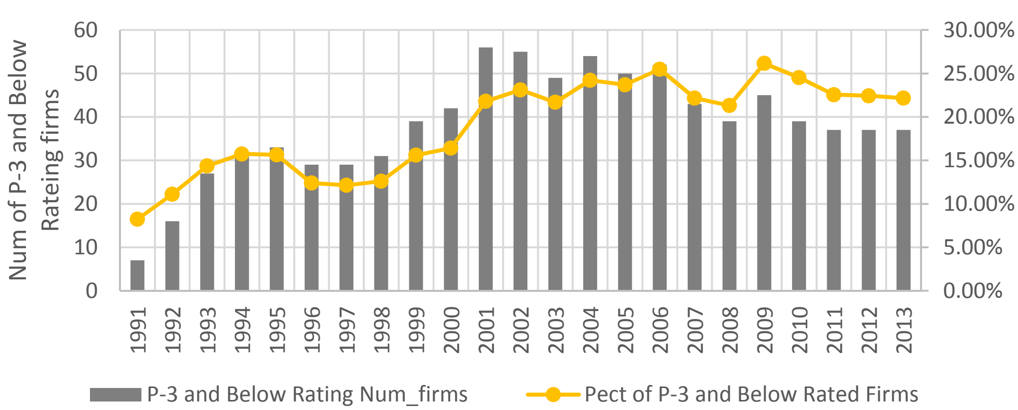
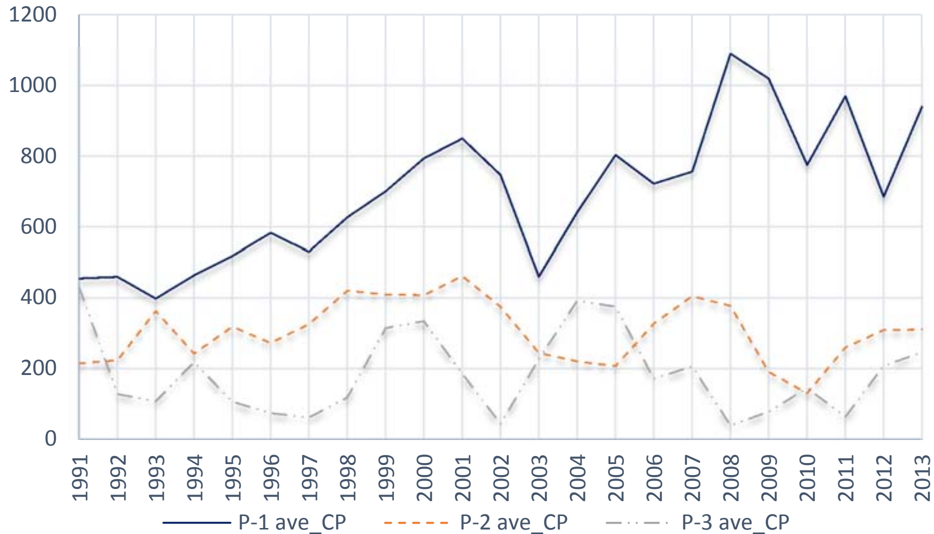


Figure 1.9 DNFCP annual issuance by rating 1991-2013

This figure plots the time series of annual average CP issuance by rating (panel A) and total CP issuance by rating (panel B).

Panel A: CP annual average issuance by rating



Panel B: CP annual total issuance by rating

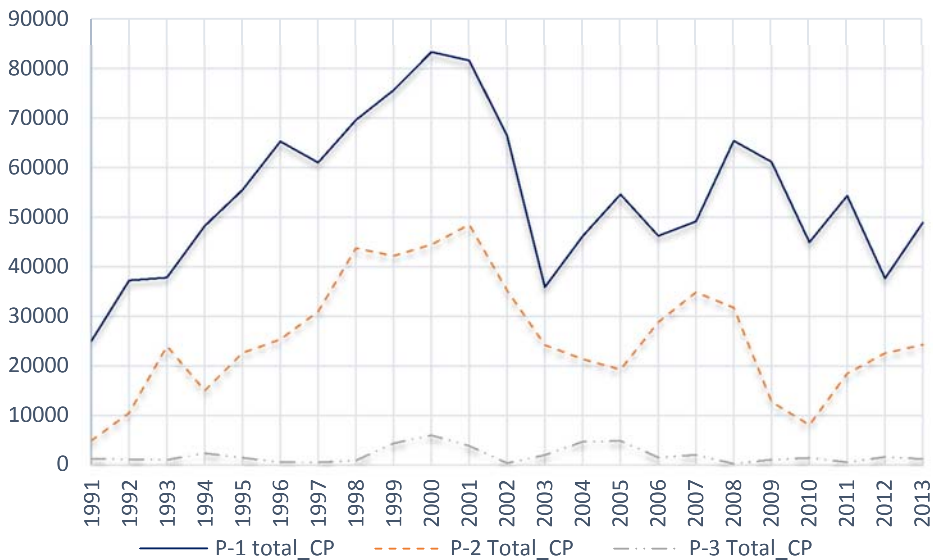
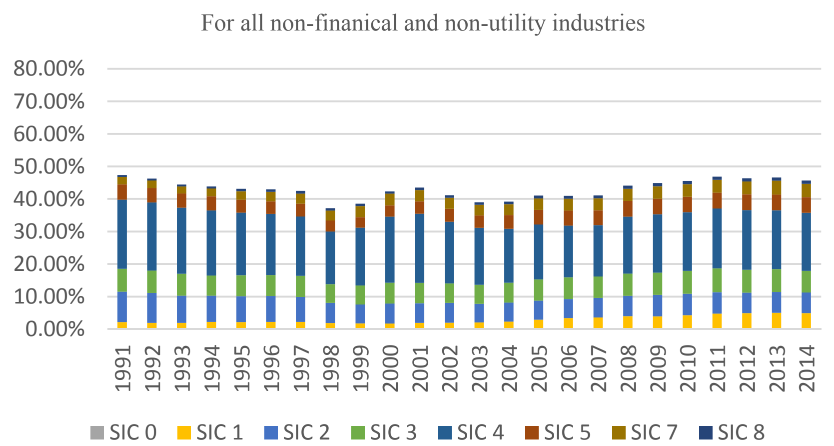
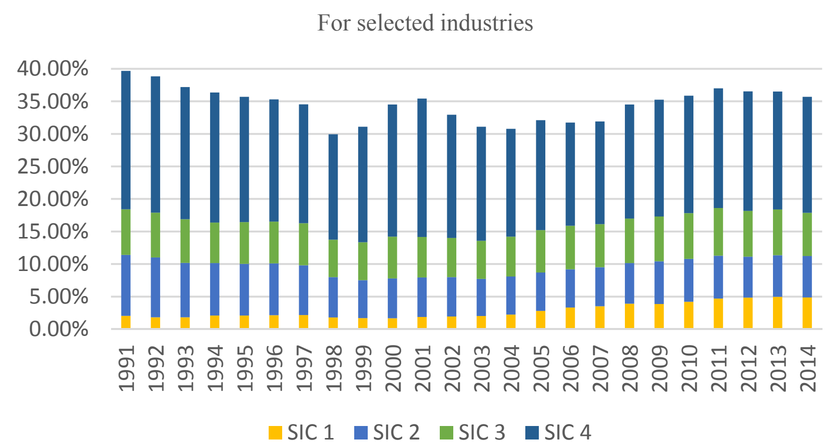


Figure 1.10 Industry composition of non-financial firms among all Compustat firms 1991-2014

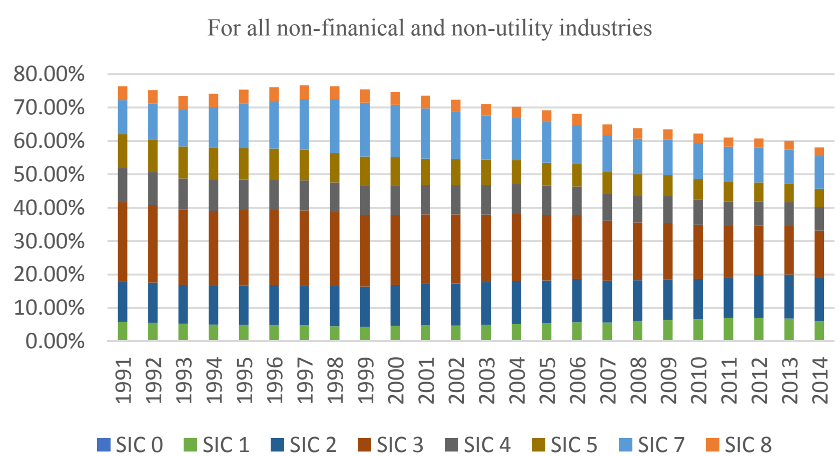
This figure plots the time series of industry composition among all Compustat firms. SIC 0: 01-09 Agriculture, Forestry and Fishing; SIC 1: 10-17 Mining and Construction; SIC 2 and SIC 3: 20-39 Manufacturing; SIC 4: 40-49 Transportation, Communications, Electric, Gas and Sanitary Services; SIC 5: 50-59 Wholesale Trade and Retail Trade; SIC 7 and SIC 8: 70-89 Services.

Panel A: Industry composition of non-financial firms among all Compustat firms (based on firms' total assets)





Panel B: Industry composition of non-financial firms among all Compustat firms (based on number of firms)



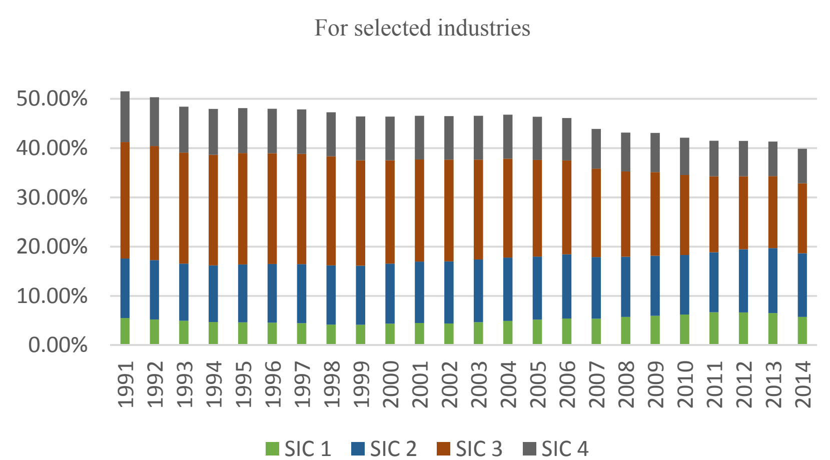
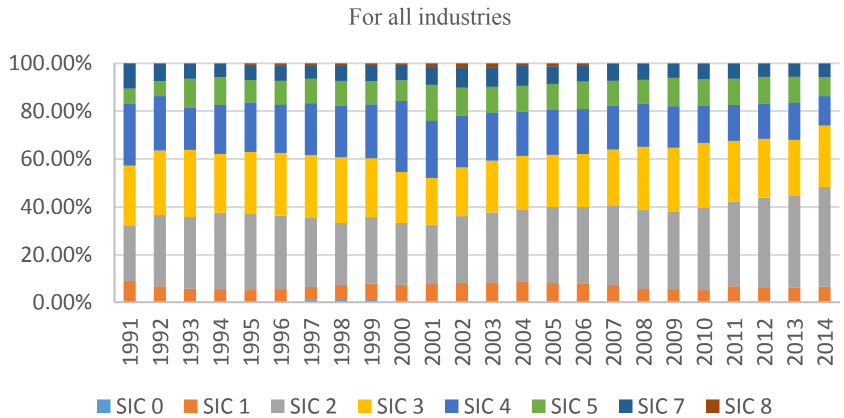
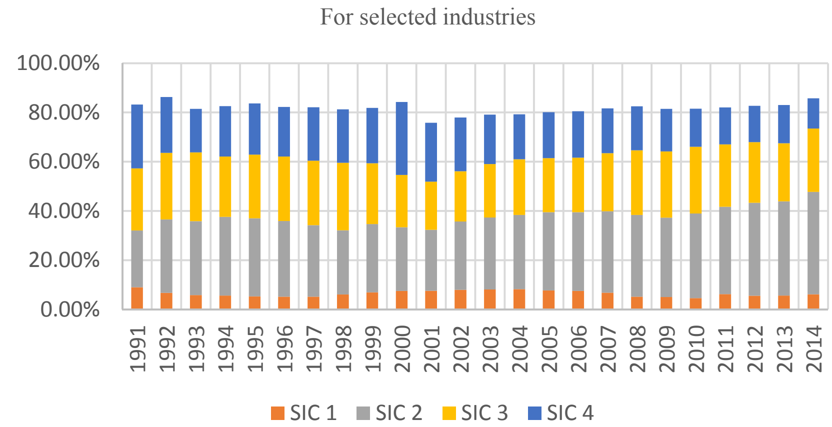


Figure 1.11 DNFCP Market Industry Composition 1991-2014

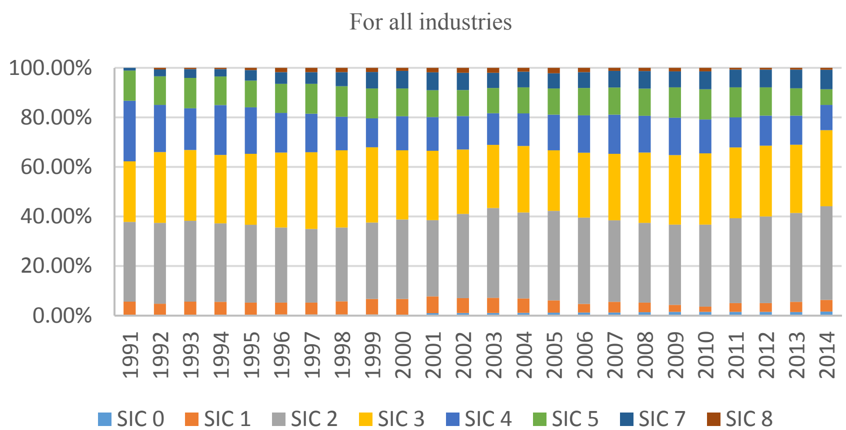
This figure plots the time series of industry composition for all firms in the DNFCP market. SIC 0: 01-09 Agriculture, Forestry and Fishing; SIC 1: 10-17 Mining and Construction; SIC 2 and SIC 3: 20-39 Manufacturing; SIC 4: 40-49 Transportation, Communications, Electric, Gas and Sanitary Services; SIC 5: 50-59 Wholesale Trade and Retail Trade; SIC 7 and SIC 8: 70-89 Services

Panel A: DNFCP market industry composition (based on firms' total assets)





Panel B: DNFCP market industry composition (based on number of firms)



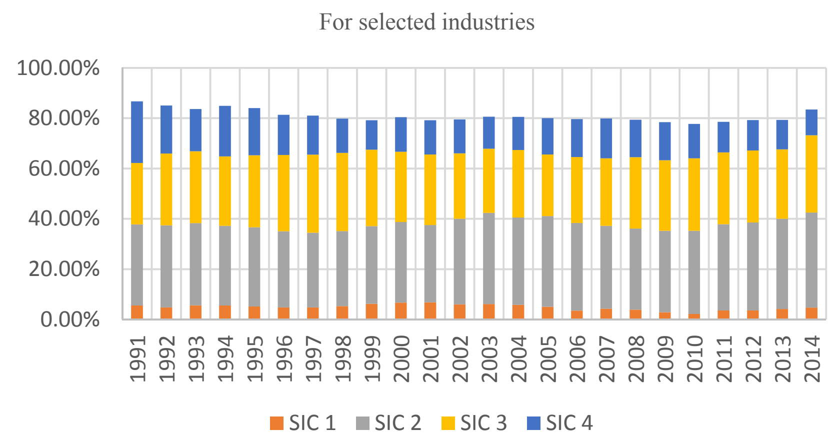


Figure 1.12 Firms with last rating as P-1 or P-2 (for Group 1 and Group 2 firms)

This figure plots the time series for the percentage of Group 1 and Group 2 firms staying or exiting the CP market (depicted on the right axis) and the total number of Group 1 and Group 2 firms in the DNFCP market (as depicted on the left axis).

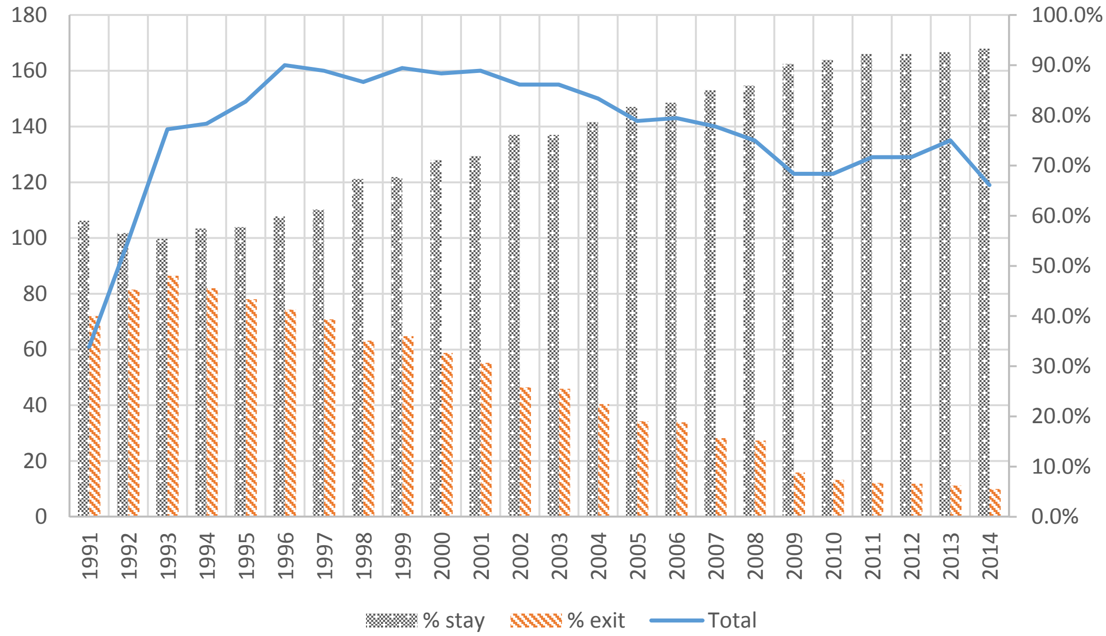


Figure 1.13 Sample firms' cash and short term investment 1991-2013

This figure plots the time series of firms' total cash holdings (scaled by lag total assets and depicted on the left axis) and the time series of the percentage of CP's outstanding compared with cash holding as depicted on the right axis.

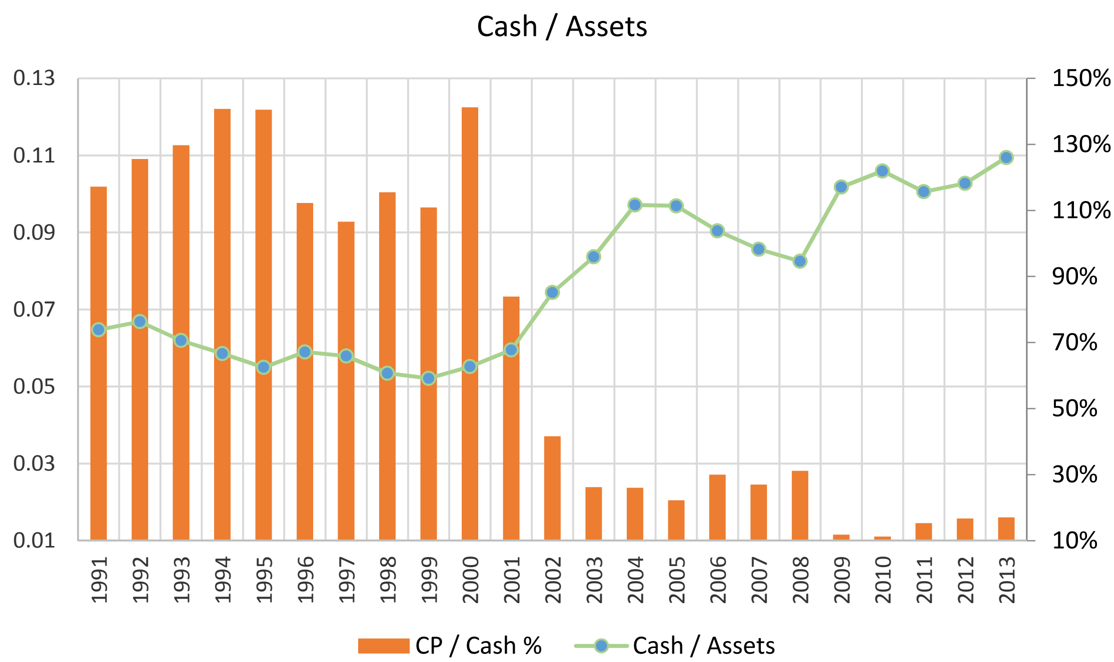
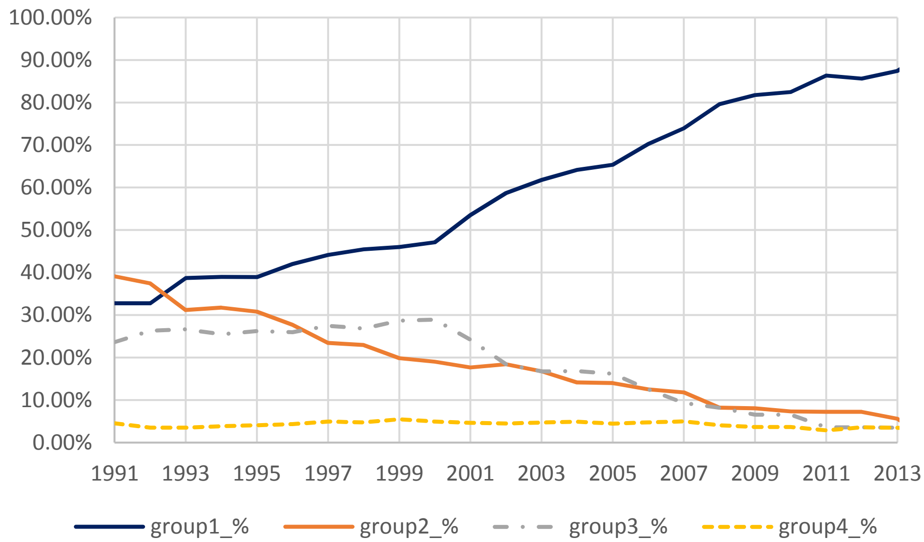


Figure 1.14 CP issuers by group from 1991 to 2013

This figure plots the time series of the percentage of firms in each group (in Panel A) and the number of firms in each group (in Panel B).

Panel A: % of firms



Panel B: Number of firms

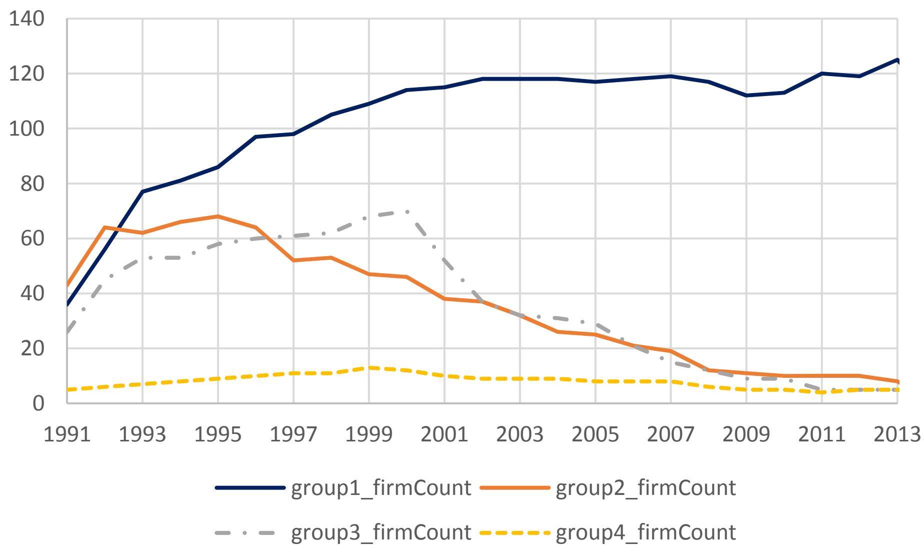


Table 1.1 Commercial paper market composition

This table reports the CP market composition. Source of data: http://www.federalreserve.gov/.

	Total Commercial Paper (Domestic + Foreign)				
	Financial CP	NonFinancial CP	Asset-backed CP	Domestic NonFinancial CP / Total CP	Domestic NonFinancial CP / NonFinaical CP
2001	41%	16%	43%	14%	90%
2002	38%	12%	49%	11%	88%
2003	39%	10%	51%	8%	86%
2004	41%	9%	50%	8%	88%
2005	41%	9%	50%	8%	88%
2006	38%	8%	54%	6%	81%
2007	39%	8%	53%	7%	84%
2008	45%	11%	44%	9%	83%
2009	46%	11%	43%	8%	71%
2010	51%	11%	38%	8%	73%
2011	50%	15%	35%	12%	79%
2012	49%	19%	32%	15%	79%
2013	52%	21%	27%	16%	75%
Average	44%	12%	44%	10%	82%

Table 1.2 Moody's short-term ratings definition

This table reports the detailed definition of Moody's short-term CP ratings.

	Moody's Short-Term Ratings
P-1	Have a superior ability to repay short-term debt obligations.
P-2	Have a strong ability to repay short-term debt obligations.
P-3	Have an acceptable ability to repay short-term obligations.
NP	Indicate that an issuer is not sufficiently protected against the possibility of short-term default under a stressed scenario.

Table 1.3 Summary Statistics

This table reports the summary statistics of all important variables used in tests of this chapter.

	N	Mean	Median	Std Dev	Minimum	Maximum
sp_rating_ave3	8222	1.4993	1.3333	0.7619	0	5
Earnings_Vol	6987	0.0741	0.0498	0.1224	0.0073	1.5327
M_B	7459	1.6824	1.3342	1.1748	0.4306	7.2618
Size (as in logSales)	7903	8.6992	8.7079	1.2679	5.4036	11.6289
Size (as in logAssets)	7931	8.7743	8.7177	1.3082	5.5668	11.8666
ChgCapex_assets	7748	-0.003	-0.0018	0.0239	-0.1008	0.0968
Capex_assets	7844	0.0597	0.048	0.0446	0.0061	0.2501
Cash_assets	7903	0.0769	0.043	0.0923	0.0002	0.4988
Inv_assets	7896	0.1159	0.0969	0.1029	0	0.4682
allindrawn	3002	76.0105	45	77.8494	15	400
Tangibility	7927	0.3412	0.2898	0.2174	0.0339	0.8935
Oper_CF_assets	7889	0.1606	0.1538	0.069	0.0168	0.3718
Leverage	7916	0.2678	0.2535	0.151	0	0.7791
Sales_growth	7819	0.079	0.0599	0.1858	-0.4955	0.9999
Working_Capital_wo_cash	7641	0.1486	0.1094	0.1904	-0.1687	1.0089

Table 1.4 Four groups of the sample

This table presents the method of the group naming and division.

	Last rating in P-1 or P-2	Last rating in P-3 or NP
Firms exit the CP market	106 (Group 2)	107 (Group 3)
Firms stay the CP market	162 (Group 1)	15 (Group4)

Table 1.5 Summary Statistics by Groups

This table reports the summary statistics of all important firm characteristics by group.

	Group 1 (N=4114)		Group 2 (N=1642)		Group 3 (N=2232)		Group 4 (N=350)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
sp_rating_ave3	1.2993	1	1.4412	1	1.8749	2	1.8709	2
Earnings_Vol	0.0738	0.0507	0.0769	0.0476	0.074	0.0498	0.0543	0.0452
M_B	1.8972	1.547	1.7201	1.3048	1.2307	1.0229	1.2587	1.1305
Size (as in logSales)	9.0336	9.0925	8.4728	8.5221	8.291	8.1324	8.4459	8.6256
Size (as in logAssets)	9.1051	9.1229	8.6498	8.7089	8.3172	8.1834	8.4258	8.4895
ChgCapex_assets	-0.0039	-0.0019	-0.003	-0.0027	-0.0015	-0.0014	-0.0009	-0.0013
Capex_assets	0.0599	0.0466	0.0658	0.0567	0.0565	0.0463	0.0508	0.0407
Cash_assets	0.0858	0.0503	0.0674	0.0331	0.0683	0.0361	0.0485	0.0252
Inv_assets	0.1174	0.1012	0.0973	0.0792	0.1285	0.1022	0.1186	0.1008
allindrawn	56.1251	35	70.3342	39.5	113.2543	75	92.5488	45
Tangibility	0.3164	0.2587	0.3981	0.3559	0.3532	0.3172	0.321	0.2474
Oper_CF_assets	0.1709	0.1657	0.1635	0.1522	0.1377	0.1308	0.1479	0.1482
Leverage	0.2436	0.2319	0.2718	0.2656	0.3021	0.2831	0.3016	0.2897
Sales_growth	0.0937	0.0707	0.0721	0.0555	0.0589	0.042	0.0541	0.0487
Working_Capital_wo_cash	0.16	0.1204	0.1182	0.0738	0.1546	0.1143	0.1133	0.0813

Table 1.6 Comparison on Firm Characteristics

This table reports the results of comparing the main firm characteristics between Group 1 and Group 2 and then Group 2 and Group 3 firms by performing t-tests. *** p<0.01,**p<0.05,*p<0.1.

	Comparison between Group 1 and Group 2			Comparison between Group 2 and Group 3		
	Group1	Group2	Paired Difference (Group1-Group2)	Group2	Group3	Paired Difference (Group2-Group3)
Size (as in logsales)	9.0336	8.4728	0.5608***	8.4728	8.291	0.1818***
Size (as in logAssets)	9.1051	8.6498	0.4553***	8.6498	8.3172	0.3326***
allindrawn	56.1251	70.3342	-14.2092***	70.3342	113.3	-42.92***
Cash_assets	0.0858	0.0674	0.0184***	0.0674	0.0683	-0.00091
Capex_assets	0.0599	0.0658	-0.00596***	0.0658	0.0565	0.00929***
Inv_assets	0.1174	0.0973	0.0201***	0.0973	0.1285	-0.0312***
Sales_growth	0.0937	0.0721	0.0216***	0.0721	0.0589	0.0132**
Oper_CF_assets	0.1709	0.1635	0.00731***	0.1635	0.1377	0.0258***
Leverage	0.2436	0.2718	-0.0281***	0.2718	0.3021	-0.0303***
Tangibility	0.3164	0.3981	-0.0817***	0.3981	0.3532	0.0448***
Earnings_Vol	0.0738	0.0769	-0.00309	0.0769	0.074	0.00289
M_B	1.8972	1.7201	0.1771*	1.7201	1.2307	0.4893*
Working_Capital_wo_cash	0.16	0.1182	0.0419***	0.1182	0.1546	-0.0364*
WC_assets	0.1309	0.0996	0.0313***	0.0996	0.1334	-0.0338***
cp_ave	576.5	398.2	178.3***	398.2	213.8	184.4***
Free_CF	0.1144	0.1239	-0.00952**	0.1239	0.101	0.0229***
Acc_payable_assets	0.0831	0.0781	0.005**	0.0781	0.0934	-0.0153***
Receivables_assets	0.1349	0.1255	0.00939***	0.1255	0.1356	-0.0101***
Div_assets	0.0246	0.0243	0.000289	0.0243	0.0166	0.00766***
TotalDebt_assets	0.2436	0.2718	-0.0281***	0.2718	0.3021	-0.0303***

Table 1.7 Group 2 Firms Long-term Rating Change 1-3 Years after Exiting the CP Market

This table reports the ratings for Group 2 firms 1-3 years after they exit the CP market.

Panel A: Number of firms in each Long-term Rating Category 1-3 years After Firm Exits the CP Market

	Last rating = P-1 Firms			Last rating = P-2 Firms		
S&P Firm Rating	1 year	2 years	3 years	1 year	2 years	3 years
1	17	14	14	16	17	18
2	4	6	6	14	14	11
3	2	2	2	8	7	5
4	3	4	0	5	1	2

Panel B: Average Long-term Firm Rating 1-3 years After Firm Exits the CP Market

	Last rating = P-1 Firms			Last rating = P-2 Firms		
	1 year	2 years	3 years	1 year	2 years	3 years
Average S&P Firm Rating	1.19	1.23	1.23	1.58	1.69	1.66

Panel C: % of Firm in each rating category 1-3 years after Firm Exits the CP Market

	P-1 Firms			P-2 Firms			Both P-1 and P-2 Firms		
S&P Firm Rating	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
1	65.38%	53.85%	63.64%	37.21%	43.59%	50.00%	54.10%	51.70%	55.20%
2	15.38%	23.08%	27.27%	32.56%	35.90%	30.56%	29.50%	33.30%	29.30%
3	7.69%	7.69%	9.09%	18.60%	17.95%	13.89%	16.40%	15.00%	12.10%
4	11.54%	15.38%	0.00%	11.63%	2.56%	5.56%	0.00%	0.00%	3.40%

Panel D: Definition of S&P Firm Rating

S&P Firm Rating	original S&P long-term firm rating
1	"A", "A+", "A-", "AA", "AA+", "AA-", "AAA”
2	BBB, "BBB+", "BBB-"
3	BB, "BB+", "BB-", "B", "B+", "B-"
4	CCC, "CCC+", "CCC-", "CC", "C"
5	D, "SD"
0	N.M.," "

Table 1.8 Probit Regressions for the Likelihood of CP Market Exit given prime-CP ratings

(Prime rating sample which includes only Group 1 and Group2)

This table shows marginal effects of probit regression predicting the likelihood of a firm exiting the CP market given that it has prime rating of P-1 or P-2. The dependent variable is one if a firm exits the CP market and zero otherwise. The sample only includes Group 1 and Group 2 firms (i.e. firms with the last rating as P-1 or P-2). *** p<0.01,**p<0.05,*p<0.1.

parameters	post-2001	pre-2001	entire sample
sp_rating_ave3	0.1924*	0.2185*	0.1701**
	(0.105)	(0.1228)	(0.0744)
Earnings Volatility t-1	0.8755	-0.362	0.2474
	(1.2941)	(0.6214)	(0.5382)
M/B t-1	-0.097	-0.0273	-0.0873*
	(0.0809)	(0.0722)	(0.0501)
Size t-1	-0.2645***	-0.15**	-0.1964***
	(0.0508)	(0.0615)	(0.0365)
lChgCapex_assets t-1	(1.6977)	-5.6964*	-2.0999
	(2.5296)	(2.9426)	(1.8212)
lCapex_assets t-1	-0.4343	-8.3696***	-3.7589***
	(1.8569)	(2.2229)	(1.343)
lCash_assets t-1	5.1881***	-1.3396	2.4549***
	(1.0626)	(1.4154)	(0.7963)
lInv_assets t-1	-0.3125	-2.9441***	-1.4126***
	(0.7083)	(0.8306)	(0.5086)
lallindrawn t-1	0.00219**	-0.00177	0.002**
	(0.00104)	(0.00168)	(0.000806)
ltangibility t-1	0.7343**	0.9748**	0.7449***
	0.3569	(0.4843)	(0.273)
lOper_CF_assets t-1	0.2836	0.7016	1.2298
	(1.1737)	(1.4228)	(0.8387)
lLeverage t-1	0.9881**	-0.8812	0.2665
	(0.4188)	(0.6015)	(0.3204)
lSales_growth t-1	-0.2115	-0.7997**	-0.4105*
	(0.3297)	(0.3331)	(0.2176)
lWorking_Capital_wo_cash t-1	-1.9274***	1.1832*	-0.5773
	(0.5487)	(0.6722)	(0.4023)
R-Square	0.1199	0.1221	0.1101
Max-rescaled R-Square	0.1969	0.1714	0.1689
N	1090	525	1716
No. of CP_Exit=1	195	165	379
No. of CP_Exit=0	895	360	1337

Table 1.9 Comparison of Capital Structure Before / After CP Market Exits

This table reports the results of t-tests comparing capital structure of the pre-exit and post-exit pairs of Group 2 firms (in Panel A) and comparing the pre-exit and post-exit pairs of Group 3 firms (in Panel A). *** p<0.01,**p<0.05,*p<0.1.

Panel A: Key Capital Structure comparison before and after exiting the CP market for Group 2 firms

	Before Exit	After Exit	Paired Difference (Before - After)
bonds (non-program, non-convertible)	0.2602	0.2196	0.0406***
Public bond	0.2109	0.1215	0.0893***
114A private placements bond	0.0319	0.0844	-0.0525***
acquisition notes	0.000668	0.00385	-0.00318***
shelf-Registered Debt	0.032	0.0116	0.0204***
Public bond / total debt	0.4766	0.2972	0.1794***
114A private placements bond / total debt	0.0419	0.1662	-0.1243***
acquisition notes / total debt	0.00196	0.0142	-0.0123***
shelf-Registered Debt / total debt	0.0603	0.0225	0.0378***

Panel B: Key Capital Structure comparison before and after exiting the CP market for Group 3 firms

	Before Exit	After Exit	Paired Difference (Before - After)
bonds (non-program, non-convertible)	0.2098	0.2534	-0.0435***
revenue bond	0.0059	0.00201	0.00389***
114A private placements bond	0.0567	0.0931	-0.0364***
Bank	0.0891	0.1172	-0.0282***
Term loan	0.0499	0.0783	-0.0284***
convertible bonds	0.0371	0.0668	-0.0297***
program debt	0.1172	0.0508	0.0664***
medium term notes	0.05	0.0171	0.0329***
private placements (excluding 144A)	0.0196	0.0355	-0.0159***
mortgage debt and equipment notes	0.00607	0.00951	-0.00345**
subordinated debt	0.0203	0.0454	-0.0251***
secured debt / total debt	0.9618	0.9088	0.053***
subordinated debt / total debt	0.0382	0.0912	-0.053***
revenue bonds / total debt	0.013	0.00567	0.00734***
114A private placements bond / total debt	0.1094	0.1633	-0.0539***
convertible bonds / total debt	0.0809	0.1423	-0.0615***
program debt / total debt	0.2308	0.1198	0.111***
medium term notes / total debt	0.0846	0.0406	0.044***
private placements / total debt	0.0439	0.0682	-0.0243***

Chapter 2

China's Delisting Rule and Its Impact on Listed Companies

2.1 Introduction

In this paper, I asked the following question: after China's 1998 accounting-based regulation on firm delisting, do Chinese loss firms take earnings management measures to improve their accounting performance?

On April 22, 1998, in order to restrain listed firms' mismanagement, Shanghai and Shenzhen Stock Exchanges announced that according to the stock listing rules, they would give special treatment to the stocks of listed companies with abnormal financial conditions. The abnormal financial condition refer to one of the following (see Javvin 2008 page 38):

1) The net profit of listed companies were negative in two consecutive fiscal years;
2) The per share net assets of listed companies in one recent year is lower than the face value of the share.
3) There is no auditing report from an authorized accounting firm, or the accounting firm's report.
4) There is any abnormal financial behavior identified and claimed by China Securities Regulatory Commission (CSRC) or a Stock Exchange.

Based on this rule, after loss for two consecutive years, if a firm does not reverse its net profit to be positive, "ST" (Special Treatment) will be added before the original share name. Additionally, it will have very limited trading privilege on the exchanges[11] and interim report will be audited. Most seriously, the ST status would greatly harm the firm's reputation. If the firm fails to turn profitable in three consecutive fiscal years, then "PT" (Particular Transfer) will be added to its stock name. If the firm doesn't recover loss for consecutive 4 years, then it will be delisted. Because of the large negative impact on firms' reputation

[11] The increase or decrease of ST share quotation is 5%.

and market liquidity, I suspect firms that receive "ST" or "PT" due to the net profit loss would have a strong incentive to reverse their losses.

Although the goal of this delisting rule is to restrain listed firms' mismanagement, the reality is that CSRC and other related regulatory authorities have adopted an administrative governance approach to regulate China's stock market and constantly make tradeoff between growth and control. For example, the administration replies on accounting numbers (e.g. ROE) to assess the readiness of IPO candidates, to approve listed firms of rights issue (i.e. to issue additional shares to existing shareholders), or to decide whether to di-list a public firm. Among all the four abnormal conditions listed above, the most important criterion for delisting a listed company is a reported net loss for four consecutive years (see Green 2003, and Pistor and Xu 2005).

Positive accounting theory predicts that when contracts are based on accounting numbers, management has an incentive to use accounting methods or other means to manipulate those numbers to serve the interests of the firm and/or its management (for a summary, see Watts and Zimmerman 1990). As in this case, I suspect that firms would have a strong incentive to change their accounting loss to profit and even resort to earnings manipulation or earnings management. So the question is whether the delisting rule really achieve what it sets out to do or whether the listed firms actually manipulate their accounting numbers to get around the rule.

Pistor and Xu (2005) documents that CSRC's heavy reliance on accounting numbers for decision making unintentionally provides the listed firms with strong incentives to manage earnings above certain thresholds. Prior literature has also documented the rampant earnings management phenomenon in Chinese listed firms stimulated by CSRC's regulations. Chen and Yuan (2004) find evidence of listed firms managing earnings for rights issues. Jian and Wong (2010) finds that a group-controlled firm in China is more likely to use related transactions to manipulate earnings and tunnel firm values. Chen et al. (2006) examines corporate financial frauds and find aspects of corporate governance that are associated with the incidence of fraud. Liu and Lu (2007) finds empirical evidence that earnings management in China is largely due to tunneling.

In this paper, I use the 1998 ST delisting mechanism used by Chinese stock exchanges as my identification strategy. With net profit being zero as the threshold set by the delisting rule, I employ an RDD (Regression-Discontinuity Design) method and analyze firms that have incurred 2 years or 3 years of continuous loss but some were just able to reverse their losses and those others who just missed the loss reversal (the so-called "borderline firms"). In particular, I examine whether the former resort to any earnings management measures to reverse their losses.

Here, I borrow the definition of earnings management from the existing accounting literature. There are generally two types of earnings management. One is called accrual manipulation and refers to managerial intervention in the reporting process. This type of manipulation generally does not generate any direct cash flow consequences. Examples include under-provisioning for bad debt expenses and delaying asset write-offs. The other type is real activity manipulation. They are managerial intervention undertaken through operational decisions and deviate from normal business practices. Real activity manipulation affect cash flows and in some cases, accruals, too. Examples of managers manipulating real activities to avoid reporting annual losses include offering price discounts to temporarily increase sales, using overproduction to report lower cost of goods sold, and reducing discretionary expenditures to improve reported margins (Roychowdhury 2006). In this paper, I will examine listed firms behavior from both angles.

The existing literature on earnings management has also provided useful tools for my research. One group of papers have identified the common characteristics of firms that engage in earnings manipulations to be employing more income-increasing account procedures, having higher total accruals, having higher estimated discretionary accruals, and more likely to have a CEO who simultaneously serves as Chairman of the Board (e.g. Dechow, Sloan and Sweeney 1996, Jensen, 1993). Another group of papers provide models and specific measures of earnings management (e.g. Jones 1991, Dechow, Sloan and Sweeney 1995, Roychowdhury 2006).

There are papers in exiting literature that have used zero earnings threshold to detect firms' earnings management behavior. The results present a mix of evidence. For example, Hayn (1995) and Burgstahler and Dichev (1997) found evidence of the discontinuity in frequency of firm-years around zero earnings. However, Dechow Dechow, Richarson and Tuna (2003) fail to find evidence that firms reporting small profits manage accruals to cross the zero threshold.

This paper contributes to the existing literature of earnings management and stock market management by testing whether firms, who are suspected to have strong motivation to cross an earnings threshold in a developing country environment, would resort to either accrual manipulation or real activity manipulation.

My research finds no evidence of borderline firms using either accrual manipulation or real activity manipulation to reverse their losses. Rather, contrary to my prior, firms that are just able to reverse loss in the third year use less non-operating net income. This is at least partially explained by the fact that the result is mainly driven by firms that have the least amount of losses in the second year.

The remainder of this paper is organized as follows. Section 2 provides some important background information of the Chinese stock market. Section 3 presents sample construction and empirical analysis. Section 4 concludes.

2.2 Institutional Background of China's Listed Companies

2.2.1. Partial privatization of State-Owned Enterprises (SOEs) and the split share structure of China's equity market

In the late 1980's, Chinese government initiated a privatization program in order to renovate its large and inefficient State-Owned Enterprises (SOEs), raise revenue for the state, provide competition and build a capital market (see Green 2003). This is followed by the establishment of Shanghai Stock Exchange in 1990 and Shenzhen Exchange in 1991.

The privatization program divided SOEs' shares into two main categories: Tradable Shares and Non-tradable Shares. Tradable shares include A-shares (Chinese Yuan – dominated), B-shares, and H-shares. Non-tradable Shares include Government Shares (which are held by the central or local governments), State Legal Person Shares (which are held by enterprises and in which the state is the majority owner), Social Legal Person Shares (which are held by domestic enterprises of which the state is not the controlling shareholder), Foreign Share, and Employee Share. The first two of the non-tradable shares together (Government Shares and State Legal Person Shares) are called State-owned Shares.

In the beginning, Tradable Shares are restricted to be no more than 25% of the firm's total capitalization which created the split share structure of China's equity market. When a firm went through IPO, only the new shares issued could be traded in the stock market and to be held by individuals and domestic institutions. However, since most listed firms are carve-outs or spin-offs from their parent SOEs, in which the original SOEs still own a large percentage of total shares of the company, the government (either central of local government) still controls the company. As a matter of fact, the newly listed firms are directly controlled by the state either through a state asset management authority or indirectly through a holding company. In most cases, managers of listed firms are even appointed directly by their parent SOEs. Before 2005, the controlling shareholders are rarely challenged by other shareholders because they own more than 44% of listed firms' shares, and publicly tradable shares only account for slightly more than 1/3rd of total outstanding shares.

After two immature and failed attempts in 1999 and 2001, CSRC successfully implemented Split-Share Structure Reform of Listed Firms on September 4, 2005. With this reform in place, after a lock-up period, the former Non-tradable shareholders can start to gradually sell off their shares based on certain rules. Specifically, through consensus with discussion and approval of majority (2/3) of the Tradable Shareholders, Non-tradable Shareholders will compensate the Tradable Shareholders through share donation, payment from retained earnings, cash, partial curtailment of Non-tradable shares, etc., to gain more shares. By June, 2007, 93% of the 1421 listed firms in China had finished their share structure reforms. (Yin, 2007).

See Table 2.1 for the composition of the company types in my sample. Before 1998, 60.1% of my sample are state-owned enterprises (including both central government and local government) and after 1998, SOE ratio drops to 34.4% while privately-owned firms increases from 29% to 57%. My baseline model is based on the post-1998 sample when the delisting rule has been in effect. This is also a period when the state ownership does not dominate the stock market which also makes a perfect setting for examining the effect of state's role on firms' performance comparing to other forms' of corporate governance.

2.2.2. The Quota system

The CSRC uses a quota system and assigns a listing quota to IPO candidates to the planning commission at the province level (Pistor and Xu, 2005). I suspect the existence of the quota system makes a loss firm's incentive to reverse loss and stay in the stock market even stronger because once a firm is out of the stock market, it could be quite hard for it to get back in line for another quota in the future.

2.3 Empirical analysis

2.3.1. Models to detect earnings manipulation

Data in this paper is from the Wind Financial Terminal (WFT) provided by Wind Information Co., Ltd (Wind Info), headquartered in Shanghai, China. The data I have used include the annual accounting information and stock prices of all listed Chinese firms on Shanghai and Shenzhen Stock Exchanges from 1990 – 2015. Final dataset consists of 2,652 firms (31,209 firm-year observation) of all non-financial Chinese companies listed on the Shanghai and Shenzhen Stock Exchanges during 1990 – 2015 with no missing total asset information. Among these firms, 948 firms have occurred losses.

Haely and Wahlen (1999) in their review of the earnings management literature, give the following definition, "Earnings management occurs when managers use judgement in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company, or to influence contractual outcomes that depend on reported accounting numbers." The definition makes it clear that it is simply not what the managers do but what their intentions are as well that make their actions count as earnings management. For example, certain activities, such as delaying or acceleration of sales, or change in shipment timing (Dechow and Skinner 2000, Haely and Wahlen 1999), if taken more than what is normal circumstances would warrant, with the goal of meeting certain earnings threshold, would be counted as earnings management.

Earnings management can be achieved by many means, such as accrual manipulation, real activity manipulation, changes in accounting methods, or changes in capital structure (Jones, 1991). This study focuses on the first two methods, studying managerial intervention in the reporting process and through operational decisions, to examine loss firms' behavior.

First, I follow The Modified Jones Model proposed in Jones (1991) and Dechow et al. (1995) to calculate nondiscretionary accruals and examine if loss firms engage in accrual manipulation to cross the zero net profit threshold. Here I use the estimate of the discretionary component of total accruals as the measure of earnings management rather than that of a single accrual. The reason is that net profit calculation uses earnings that involves the effects of all accrual accounts and managers are likely to use several of them to increase reported earnings. As explained in Jones (1991), total accrual (TA) includes changes in working capital accounts, such as accounts receivable, inventory and accounts payable, which all depend to some extent on changes in revenues. Therefore, as in equation (2), the expectation model for calculating TA includes revenues (REV) as a control for economic environment of the firm. Although they are not completely exogenous, they are at least an objective measure of the firms' operations *before* managers' manipulations. Gross property, plant and equipment (PPE) is the second variable that is included in the model as control for the portion of total accruals related to nondiscretionary depreciation expense. Then, on both sides of the model, all variables are scaled by lagged assets in order to reduce heteroscedasticity.

The idea of using this model is that managers of loss firms would benefit from reporting positive net profit in the third (or fourth) year by making accounting choices that increases the reported earnings during the third or fourth year when earnings management are most likely to happen as compared to all the other years.

I first calculate total accruals (TA) using variables from my dataset based on formula (1). Then I run an OLS regression using model (2) in the "estimation period" (i.e. period in which no systematic earnings management is hypothesized) to generate the parameters $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\alpha}_3$ for (3). The estimation period for my sample includes post 1998 period excluding year 3 (or year 4) after a firm has incurred 2 years (or 3 years) of continuous loss. I then input the OLS estimates from (2) into (3) and calculate the NDA (nondiscretionary accruals) in the "event period" (i.e. period when earnings management is hypothesized). In this case, my event period sample includes post 1998 observations that only include year 3 (or year 4) after a firm incurs 2 years (or 3 years) of continuous loss. Then, I calculate DA (discretionary accruals) using model (4). If firms have statistically significant amount of DA in loss reversal years, then it indicates that firms engage in earnings manipulation. Equation (5) calculates the predicted profit (or non-managed profit) by subtracting DA from net profit.

$$TA_t = NetProfit_t - CFO_t \text{ (1)}$$

$$\frac{TA_t}{A_{t-1}} = \alpha_1\left(\frac{1}{A_{t-1}}\right) + \alpha_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \alpha_3\left(\frac{PPE_t}{A_{t-1}}\right) + v_1 \text{ (2)}$$

$$\frac{NDA_t}{A_{t-1}} = \hat{\alpha}_1(\frac{1}{A_{t-1}}) + \hat{\alpha}_2(\frac{\Delta REV_t}{A_{t-1}} - \frac{\Delta REC_t}{A_{t-1}}) + \hat{\alpha}_3(\frac{PPE_t}{A_{t-1}}) \text{ (3)}$$

$$DA_t = TA_t - NDA_t \text{ (4)}$$

$$NonManagedProfit_t = NetProfit_t - DA_t \text{ (5)}$$

$$where\text{: } A_{t-1} = Total\ Assets_{t-1}, \Delta REV_t = REV_t - REV_{t-1}\ , \Delta REC_t = REC_t - REC_{t-1}$$

$$\alpha_1, \alpha_2\ and\ \alpha_3\ are\ the\ OLS\ estimates\ of\ \hat{\alpha}_1, \hat{\alpha}_2\ and\ \hat{\alpha}_{3.}$$

$$TA_t = TotalAccrual_t,\ NDA_t = NonDiscretionaryAccrual_t$$

$CFO, REV, REC\ and\ PPE$ stand for operating cash flow, revenues, net receivables, and gross property, plant and equipment respectively. Table 2.3 column (4) reports the regression coefficients for model (2). My results match the coefficients from Jones (1991) in signs and magnitude.

Next, I follow Roychowdhury (2006) to detect if loss firms engage in real activities manipulations to cross the zero net profit threshold. Here, I want to detect the occurrence of the following three manipulation activities: 1) Abnormal cash flow from operation. Cash flow from operation (CFO) refers to the same item as reported in the statement of cash flow. The abnormal CFO can be caused by sales manipulation, for example, accelerating the timing of sales and / or generating additional sales through increased price discounts or other credit terms; 2) Abnormal discretionary expenses. This can be achieved by abnormally reducing discretionary expenditures, which includes advertising expenses, R&D expenses, and selling, general and administrative (SG&A) expenses; 3) Abnormal production costs. Production costs (PROD) are the sum of cost of goods sold (COGS) and change in inventory. The abnormal PROD can be caused by over production or by reporting lower COGS through increased production. Roychowdhury (2006) finds evidence suggesting price discounts to temporarily increase sales, overproduction to report lower COGS, and reduction of discretionary expenditures to improve reported margins.

The idea of behind using this model is that managers of loss firms would benefit from making real activities manipulation in order to bring their net profit to be positive in the third (or fourth) year as compared to all the other years. Following is the model.

$$\frac{CFO_t}{A_{t-1}} = \beta_0 + \beta_1(\frac{1}{A_{t-1}}) + \beta_2(\frac{Sales_t}{A_{t-1}}) + \beta_3(\frac{\Delta Sales_t}{A_{t-1}}) + \varepsilon_t \text{ (6)}$$

$$\frac{DISEXP_t}{A_{t-1}} = \beta_0 + \beta_1(\frac{1}{A_{t-1}}) + \beta_2(\frac{Sales_{t-1}}{A_{t-1}}) + \varepsilon_t \text{ (7)}$$

$$\frac{PROD_t}{A_{t-1}} = \beta_0 + \beta_1(\frac{1}{A_{t-1}}) + \beta_2(\frac{Sales_t}{A_{t-1}}) + \beta_3(\frac{\Delta Sales_t}{A_{t-1}}) + \beta_4(\frac{\Delta Sales_{t-1}}{A_{t-1}}) + \varepsilon_t \text{ (8)}$$

$$where\ PROD_t =\ COGS_t +\ \Delta INV_t$$

$$where\text{: } A_{t-1} = Total\ Assets_{t-1}, \qquad \Delta Sales_t = REV_t - REV_{t-1}$$

I first calculate the predicted operating cash flow (CFO), production costs (PROD) and discretionary expenses (DISEXP) using the OLS estimates from regression results of (6), (7) and (8) which are run for every industry and year. Then I use the estimated coefficients to calculate the normal (or predicted levels. Finally, I calculate the difference between the actual values and the predicted values to get abnormal values for CFO, PROD and DISEXP. Table 2.3 columns (1) – (3) report the regression coefficients for the normal or predicted levels of CFO, PROD and DISEXP. The coefficients in my paper are generally as predicted by Roychowdhury (2006) in sign and magnitude.

Additionally, among the variables firms use in calculating net profit, I examine 13 of them that are likely to be manipulated in order for firms to cross the zero net profit threshold: sales, COGS, sales tax, sales expense, administrative expense, finance expense, depreciation, P/L (Profit/Loss) in fair value change, P/L in investment, income tax, operating profit, total profit, and non-operating net income.

Finally, I check 2 other variables to measure firms' performance: EPS and diluted EPS.

In the following sections (sections 3.2 – 3.5), I use four different methods to examine whether the year 3 (after 2 years of continuous loss) or year 4 (after 3 years of continuous loss) firms engage in earnings management by running the following regression (9):

$$Y_t = \alpha_i + \beta_1 Net\_Income_{t-1} + \beta_2 Treat_t \quad (9)$$

Y_t includes total accrual from (1), discretionary accrual from (4), abnormal operating cash flow, abnormal discretionary expenses, and abnormal production costs calculated from Roychowdhury (2006) model, and fifteen other variables as mentioned above (all scaled by lagged one year total assets): sales, COGS, sales tax , sales expense, administrative expense, finance expense, depreciation, P/L in fair value change, income tax, operating profit, total profit, P/L in investment, non-operating net income, EPS, and diluted EPS.

2.3.2. Method 1 - RDD

I have two post-1998 samples. Sample 1 include all firms that have incurred 2 continuous years of loss and their net profit in the third year are within the range of median of negative net profit and median of positive net profit. This results 321 firms, with 225 treated and 96 untreated. I define a firm's treated status as $Treat = 1$ if its net_profit ≥ 0 which indicates that firm reverses loss in year 3 or year 4. $Treat = 0$ otherwise. Sample 2 includes all firms that have incurred 3 continuous years of loss and their net profit in the fourth year are within the range of median of negative net profit and median of positive net profit. This results 88 firms, with 54 treated and 34 untreated.

Because the two groups of firms' vicinity to the zero net profit delisting (for 3 year loss sample) or no trading (for 2-year loss sample) threshold, they should have very similar financial characteristics. This is verified by t-tests on treated and untreated firms' main financial parameters as shown in Table 2.4. None of the characteristics are significantly different between the two groups of firms.

As indicated in Table 2.5, after running regressions model (9) for sample 1, I find that except for EPS and diluted EPS, none of the other tests have statistically significant results to indicate earnings management (only selected results are listed here). I use the same method for sample 2 and get similar results.

In summary, it is apparent that most firms that have incurred 2 years of loss reverse their losses in year 3 instead of year 4. This may be due to the strong negative signal the designation of "ST" sends to the market regarding the firms' financial situation and this gives the firms strong incentive to reverse their loss. However, so far, there is no indication that firms have resorted to earnings management, either through earnings manipulation or real activities.

For the rest of the paper, I will focus on loss reversal for year 3 firms because of the very small sample size for year 4 firms.

2.3.3. Method 2 - RDD with propensity score (PS) matching

Next, I use propensity score matching to create a matching sample before applying RDD method. Propensity Scores (PS) for treated (loss reversed) and control (not reversed) firms are calculated by following model (10) regression.

$$Treat_t = \alpha_i + \gamma_1 Size_{t-1} + \gamma_2 Zscore_{t-1} + \gamma_3 \frac{NetProfit_{t-1}}{A_{t-1}} + \gamma_4 Leverage_{t-1} + year + industry_i \quad (10)$$

I match each pair of firms by choosing the minimum difference in their respective propensity scores and allow repeated use of control firms. This leads to 224 pairs of firms (see Table 2.6 Panel A). I then use the RDD method and choose only matching firms that are within the range of the median of negative net profit to median of positive net profit to form the full PS sample.

Regression results for Model 9 by using this sample show that only non-operating net income and P/L from investment have statistically significant results (only significant results are reported). Non-operating income measures firms' non-operating activities. The components of non-operating income, such as profits from the sale of fixed assets or investments, have been shown to be tools of earnings management in the U.S. (e.g., Bartov 1993) and other countries, including Japan (Herrmann et al. 2003) and Singapore (Poitras et al. 2002). However, the coefficients on Treat for both measures (see Table 2.7 columns a and b, and Figure 2.1) have negative sign, which indicate that treated firms have less non-operating net income and less profit from investment. This implication is quite puzzling.

As robustness check, I create a so-called below-mean PS sample by selecting the PS matching pairs that have PS difference below the sample mean (see Table 2.6 panel B) and then apply the RDD method. Results are similar to the PS full sample (see Table 2.7 columns c and d and Figure 2.1).

2.3.4. Method 3 – Robustness check 1 - Propensity matching only

In the first robustness check, I use the full PS sample created from section 2.3.3 without excluding any firms and run model 9 with the 20 different dependent variables. The result (see Table 2.8 Panel A and Figure 2.2 (1) – (5)) shows that treated firms have less abnormal discretionary expenses, less total profit but more operating profit, less depreciation, and less administrative expense.

When using the below-mean PS sample, the result is consistent (see Table 2.8 Panel B), except that this time the result also indicates that treated firms have less non-operating net income (see Figure 2.2. (6)) which is consistent with Method 2.

2.3.5. Method 4 - Robustness check 2 - RDD with industry and year matching

As a further check, I use year and 2 digit SIC industry code matching to create my matching pairs. Then I apply the RDD method by selecting only firms within the median of net profit on both sides of the zero net profit threshold. The result is consistent with Method 1 and 2 (see Table 2.9).

2.3.6. Further discussion on Method 2

Although there are somewhat different results from Method 1 – 4, one robust result is for non-operating net income. By using method 2 sample, next I explore the source of this result.

Based on year 2's loss, I separate sample firms into 4 loss levels corresponding to 25, 50, 75 percentiles and name it level 1 to 4 with level 1 as having the smallest amount of loss (scaled by beginning of year total assets). I expect the loss level in year 2 to have an impact on firms' reversal in year 3. The results in Table 2.10 show that the reason why loss reversed firms have significantly less non-operating net income is mainly driven by firms that have 25 percentile of loss or less in year 2. Firms above 75 percentiles of loss in year 2 appear to drive the result for P/L from investment. For robustness check, I also run the test separating the sample into 5 loss levels based on year 2 loss. The results are similar.

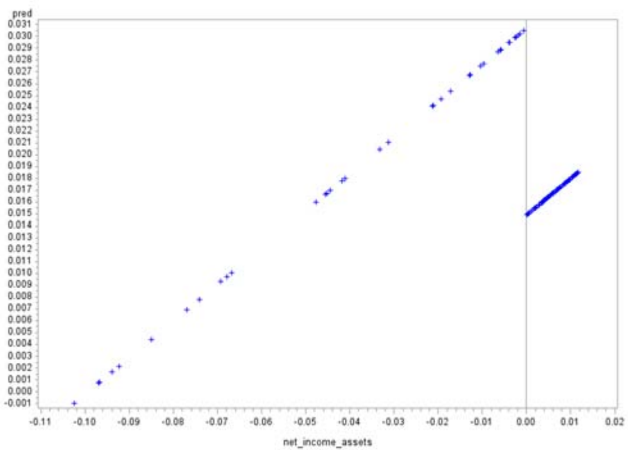
2.4 Conclusions

In summary, this research find no evidence of firms that are just able to reverse its loss in year 3 using either accrual manipulation or real activity manipulation to reverse their losses. Rather, contrary to my prior, the result shows that firms that are just able to reverse loss in the third year use less non-operating net income. This is at least partially explained by the fact that the result is mainly driven by firms that have the least amount of losses in the second year. Those firms likely are able to reverse their losses without resorting to extreme measures.

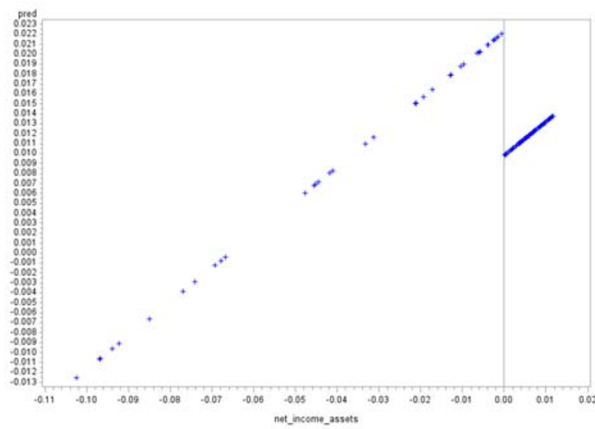
2.5 Tables and Figures

Figure 2.1 Non-parametric models for post-1998 sample to test the jump at the cutoff (For RDD with Propensity Score Matching)

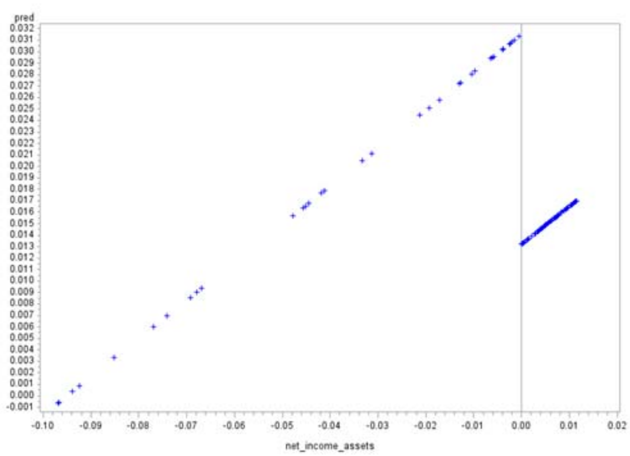
This figure plots no-operating net income, P/L from investment on the threshold variable net profit (scaled by beginning of year total assets) both for the full propensity score sample and for the below mean propensity score sample).



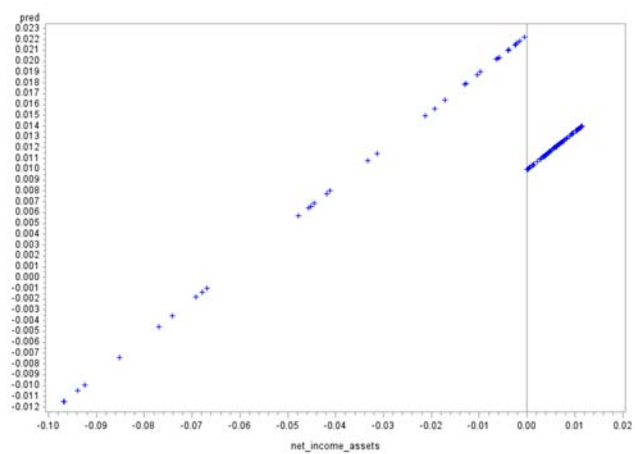
(1) Predicted non-operating net income on net profit (full PS Sample)



(2) Predicted P/L from Investment on net profit (full PS Sample)



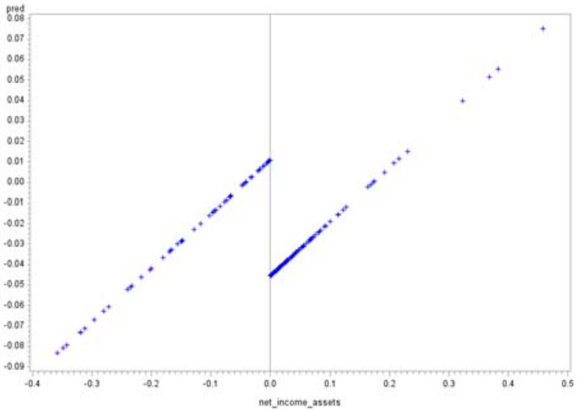
(3) Predicted non-operating net income on net profit (Below mean PS Sample)



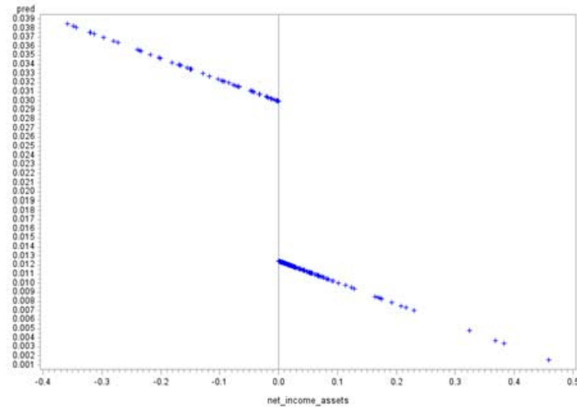
(4) Predicted P/L from Investment on net profit (Below mean PS sample)

Figure 2.2 Non-parametric models for post-1998 sample to test the jump at the cutoff (For Propensity Score Matching only)

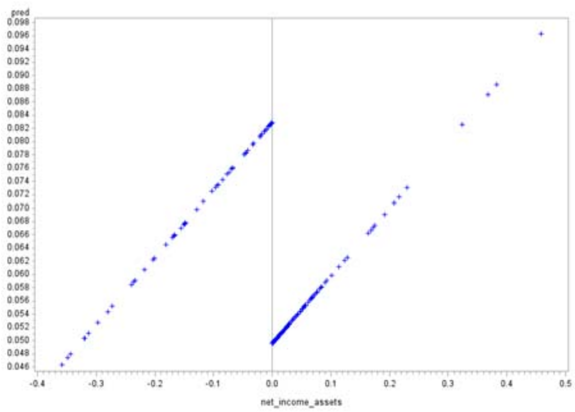
This figure plots abnormal discretional expenses, depreciation, administrative expenses, operating profit and total profit on the threshold variable net profit (scaled by beginning of year total assets) for the full propensity score sample; and non-oprating net-income on the threshold variable net profit (scaled by beginning of year total assets) for the below mean propensity score sample).



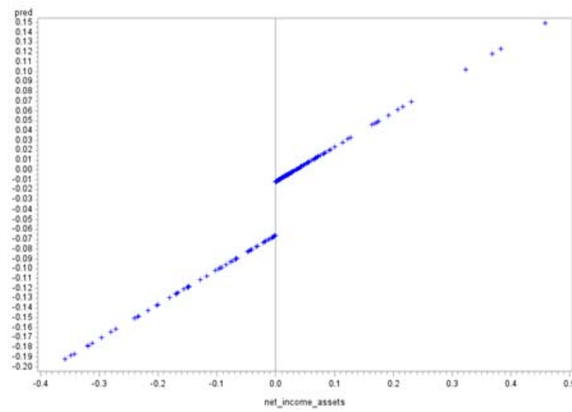
(1) Predicted abnormal DISEXP on net profit (full PS Sample)



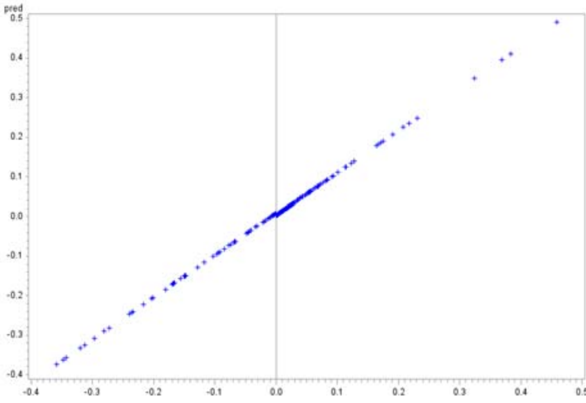
(2) Predicted Depreciation on net profit (full PS sample)



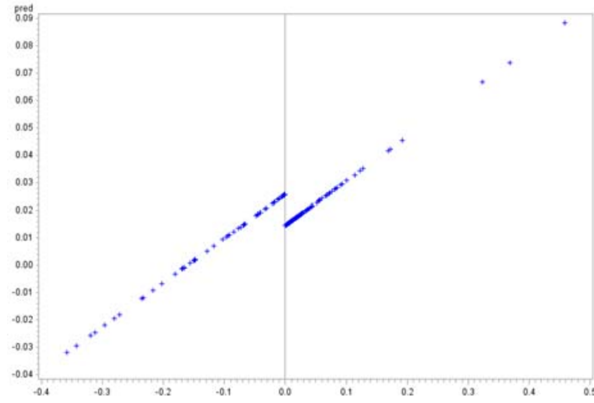
(3) Predicted Administrative Expenses on net profit (full PS Sample)



(4) Predicted Operating Profit on net profit (full PS sample)



(5) Predicted Total Profit on net profit (full PS Sample)



6) Predicted Non-operating Net Income on net profit (Below mean PS sample)

Table 2.1 Firm Types

This tables shows the number of firms in each company type. The numbers in the brackets represent the percentages of firms in each column category.

Company Type	Pre-1998	Post-1998	All
State_Central	189	343	343
	(19.6%)	(12.6%)	(12.6%)
State_Local	389	596	596
	(40.4%)	(21.9%)	(21.9%)
Private	279	1554	1554
	(29.0%)	(57.0%)	(57.0%)
Collective	53	117	117
	(5.5%)	(4.3%)	(4.3%)
Foreign	29	81	81
	(3.0%)	(3.0%)	(3.0%)
Other	23	35	35
	(2.4%)	(1.3%)	(1.3%)
total	962	2726	2726

Table 2.2 Number of firms based on industry

This table shows the industry composition of the sample.

CSRC Industry Category	Number of firms
Manufacturing	1822
Technology	166
Wholesale retail	156
Energy	93
Transportation	90
Construction	80
Mining	76
Agriculture	48
Sports and Entertainment	39
Uncategorized	34
Environment	31
Comprehensive	30
Commercial Services	26
Science	22
Real Estate	13
Hospitality	11
Health care	5
Education	1
Total	2743

Table 2.3 Model Coefficients

This table reports the estimated coefficients for models (2), (6), (7) and (8). Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	CFO_t/A_{t-1}	$DisExp_t/A_{t-1}$	$Prod_t/A_{t-1}$	NDA_t/A_{t-1}
Intercept	-0.0016	0.0838***	-0.0476***	0.0273***
	(0.0064)	(0.0057)	(0.0104)	(0.0068)
$1/A_{t-1}$	5.9140***	20.1036***	-25.4347***	1.4538***
	(0.3286)	(0.3328)	(0.5628)	(0.3533)
$Sales_t/A_{t-1}$	0.0328***		0.8994***	
	(0.0012)		(0.0020)	
$Sales_{t-1}/A_{t-1}$		0.0338***		
		(0.0008)		
$\Delta Sales_t/A_{t-1}$	0.0437***		-0.0229***	0.0608***
	(0.0029)		(0.0045)	(0.0024)
$\Delta Sales_{t-1}/A_{t-1}$			-0.0370***	
			(0.0036)	
PPE_{t-1}/A_{t-1}				-0.1046***
				(0.0031)
R^2	0.1360	0.2392	0.9388	0.1127

Table 2.4 Method 1 - Comparison of main characteristics for treated and untreated firms ("borderline" firms)

This table reports the t-test results on important firm characteristics for treated firms (firms that become profitable after 2 or 3 years of continuous of loss) and untreated firms (firms that continue to incur loss after 2 or 3 years of continuous loss) for the sample used in Method 1. Note: Total assets are in millions of Chinese Yuan. Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	Sample 1: 3 year median sample			Sample 2: 4 year median sample			Sample 1 robustness check: 3 year 25 percentile sample		
	0	1	diff	0	1	diff	0	1	diff
Total_assets	3,420.900	3,866.400	-445.500	1,984.800	2,371.800	-387.000	3787.7	3910.9	-123.2
			(1426.3)			(1336.4)			(1542.5)
ROA	-0.137	-0.144	0.008	-0.183	-0.252	0.069	-0.133	-0.110	-0.024
			(0.032)			(0.0896)			(0.0271)
leverage	0.491	0.393	0.097	0.426	0.550	-0.124	0.551	0.371	0.180
			(0.0744)			(0.1234)			(0.1309)
WC_assets	-0.271	-0.231	-0.040	-0.417	-0.371	-0.045	-0.276	-0.174	-0.101
			(0.0836)			(0.1167)			(0.1184)
Sales_assets	0.446	0.459	-0.013	0.415	0.391	0.024	0.496	0.467	0.030
			(0.0466)			(0.1032)			(0.0731)
Zcore	-2.711	-2.265	-0.446	-4.225	-4.002	-0.223	-2.970	-1.445	-1.525
			(0.7552)			(1.4152)			(1.0573)
N	96	225		34	54		48	113	

Table 2.5 Method 1 - RDD non-parametric model results for 3-year median sample

This table reports selected results for model (9) $Y_t = \alpha_i + \beta_1 Net\_Income_{t-1} + \beta_2 Treat_t$ with Method 1 sample. Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
	TA	DA	Ab CFO	Ab PROD	Ab DISEXP	EPS	Diluted EPS
Net income/assets	0.8666***	0.8463***	0.3709*	-0.0077	-0.2891	380.1682***	384.5996***
	(-0.1651)	(0.169)	(0.2052)	(0.1826)	(0.2821)	(-21.8793)	(-22.4463)
treat	-0.0145	-0.0164	-0.0066	-0.0197	-0.0054	-6.1703***	-6.3902***
	(-0.0165)	(0.0167)	(0.0205)	(0.0182)	(0.0277)	(-1.9943)	(-2.0527)

Table 2.6 Method 2 - Non Parametric RDD Models with Propensity Score Matching – PS Comparison

This table shows the propensity scores for treated and untreated (i.e. control) firms and their PS score difference for both the PS sample (Panel A) and the below-mean PS sample (Panel B).

Panel A: PS sample - Estimated Probability Comparison

	N	Mean	Median	Std Dev	Minimum	25th Pctl	75th Pctl	90th Pctl	Maximum
ps_control	224	0.7315	0.7301	0.1705	0.1081	0.6488	0.8761	0.9341	1.0000
ps_treat	224	0.7272	0.7311	0.1645	0.0872	0.6492	0.8731	0.9352	0.9352
ps_diff	224	0.0079	0.0026	0.0154	0.0000	0.0012	0.0060	0.0182	0.0648

Panel B: Below-mean PS sample - Estimated Probability Comparison

	N	Mean	Median	Std Dev	Minimum	25th Pctl	75th Pctl	90th Pctl	Maximum
ps_control	177	0.6956	0.6973	0.1379	0.1792	0.6320	0.7830	0.9027	0.9421
ps_treat	177	0.6957	0.6948	0.1383	0.1767	0.6323	0.7799	0.9086	0.9352
ps_diff	177	0.0023	0.0021	0.0017	0.0000	0.0010	0.0033	0.0044	0.0070

Table 2.7 Method 2 - Non Parametric RDD Models with Propensity Score Matching

This table reports statistically significant results for model (9) $Y_t = \alpha_i + \beta_1 Net\_Income_{t-1} + \beta_2 Treat_t$ with Method 2 sample. Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	Full PS sample		Below mean-diff PS sample	
	(a)	(b)	(c)	(d)
	Non-op net-income	PL investment	Non-op net-income	PL investment
Intercept	0.0307***	0.0223***	0.0315***	0.0224***
	(0.0079)	(0.0066)	(0.0077)	(0.0063)
net_income_assets	0.3090*	0.3397***	0.3315**	0.3499***
	(0.1611)	(0.1297)	(0.1579)	(0.1292)
treat	-0.0158*	-0.0125*	-0.0183**	-0.0124*
	(0.0091)	(0.0077)	(0.0091)	(0.0074)
n	124	143	104	119

Table 2.8 Method 3 - Robustness Check 1: Propensity Matching Only

This table reports statistically signifcant results for model (9) $Y_t = \alpha_i + \beta_1 Net\_Income_{t-1} + \beta_2 Treat_t$ with Method 3 sample. Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Full PS sample

	Ab DISEXP	Total profit/assets	Operating Profit/assets	Depreciation/assets	Expense admin/assets
Intercept	0.01103	0.0092***	-0.0658***	0.0300***	0.0829***
	(0.01253)	(0.0016)	(0.0107)	(0.0041)	(0.0069)
net income/assets	0.26313***	1.0660***	0.3520***	-0.0237	0.1019***
	(0.05565)	(0.0067)	(0.0468)	(0.0177)	(0.0302)
treat	-0.05643***	-0.0059***	0.0540***	-0.0175***	-0.0334***
	(0.01484)	(0.0019)	(0.0126)	(0.0049)	(0.0081)
n	282	314	295	223	295

Panel B: Below mean-diff PS sample

	Ab DISEXP	Total profit/assets	Operating Profit/assets	Depreciation/assets	Expense admin/assets	Non-op net income / assets
Intercept	0.0062	0.0077***	-0.0676***	0.0294***	0.0805***	0.0259***
	(0.0119)	(0.0016)	(0.0101)	(0.0044)	(0.0071)	(0.0050)
net income/assets	0.2379***	1.0593***	0.3366***	-0.0291	0.0926***	0.1611***
	(0.0582)	(0.0069)	(0.0486)	(0.0204)	(0.0343)	(0.0245)
treat	-0.0526***	-0.0047**	0.0544***	-0.0163***	-0.0305***	-0.0113*
	(0.0142)	(0.0019)	(0.0121)	(0.0053)	(0.0085)	(0.0060)
n	238	260	245	180	245	197

Table 2.9 Method 4 - Robustness Check 2: Firm Year Matching with RDD Median Sample

This table reports statistically significant results for model (9) $Y_t = \alpha_i + \beta_1 Net\_Income_{t-1} + \beta_2 Treat_t$ with Method 4 sample. Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

Year and Industry Matching Sample with RDD Median

	EPS Diluted / assets	EPS / assets	Non-op net income / assets
Intercept	0.0001***	0.0001***	0.0264***
	(0.00002)	(0.00002)	(0.00599)
net income/assets	0.0035***	0.0035***	0.2062***
	(0.00023)	(0.00022)	(0.06720)
treat	-0.0001***	-0.0001***	-0.0111
	(0.00002)	(0.00002)	(0.00686)
n	169	174	199

Table 2.10 Method 2 sample loss level check

This table reports results for model (9) $Y_t = \alpha_i + \beta_1 Net\_Income_{t-1} + \beta_2 Treat_t$ by dividing Method 2 sample into 4 levels based on their net profit in 2nd year. Based on year 2's loss, sample firms are divided into 4 loss levels corresponding to 25, 50, 75 percentiles and are named as level 1 through 4 with level 1 as having the smallest amount of loss (scaled by beginning of year total assets). Standard errors are reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Full PS sample

	Non-op net income / assets				P/L investment / assets			
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	level 1	level2	level3	level4	level 1	level2	level3	level4
Intercept	0.0359***	0.0103	0.0243	0.0450	0.0166**	0.0198	0.0165	0.0677**
	(0.0088)	(0.0232)	(0.0170)	(0.0261)	(0.0090)	(0.0140)	(0.0137)	(0.0261)
Net income / assets	0.3875**	0.4140	-0.0214	0.4764	0.2425	0.2935	0.5207	0.8949*
	(0.1615)	(0.7813)	(0.5403)	(0.4556)	(0.1658)	(0.2629)	(0.4345)	(0.4535)
treat	-0.0350***	0.0052	-0.0007	-0.0201	-0.0079	-0.0089	-0.0076	-0.0603*
	(0.0105)	(0.0272)	(0.0210)	(0.0293)	(0.0109)	(0.0155)	(0.0168)	(0.0296)
	42	31	42	31	47	33	47	33

Panel B: Below mean PS sample

	Non-op net income / assets				P/L investment / assets			
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	level 1	Level 2	Level 3	Level 4	level 1	Level 2	Level 3	Level 4
Intercept	0.0359***	0.0120	0.0251	0.0470*	0.0164**	0.0200	0.0165	0.0664**
	(0.0097)	(0.0204)	(0.0175)	(0.0251)	(0.0061)	(0.0151)	(0.0144)	(0.0261)
Net income / assets	0.3880**	0.4983	0.0173	0.5212	0.2376**	0.3009	0.5189	0.8648*
	(0.1775)	(0.6932)	(0.5558)	(0.4389)	(0.1115)	(0.2852)	(0.4579)	(0.4554)
treat	-0.0357***	-0.0003	0.0000	-0.0291	-0.0087	-0.0077	-0.0078	-0.0593*
	(0.0118)	(0.0241)	(0.0217)	(0.0291)	(0.0075)	(0.0169)	(0.0179)	(0.0301)
	35	26	27	15	40	28	30	21

Chapter 3

Soft Information and Internal Credit Ratings of Bank Loans

3.1 Introduction

How do banks make their loan decisions? Why do we care about it? I think the importance of examining the loan determinants and their effectiveness for bank decision-making lies in at least the following three aspects. First of all, bank is one of the major players in a country's economy. Bank financing has been identified as the prime source of a firm's external financing in all countries (Mayer 1990, Jacobson et al. 2006). The importance of bank and its role in a country's economy is further exemplified in the 2008 financial crisis. Therefore, examining the inputs for banks' ex-ante assessment of loan applications and the effectiveness of its loan decision making not only can help us understand banks' behavior but also corporations' financing behavior. Secondly, from the banks' point of view, evaluating the effectiveness of current bank lending procedures are important for banks' own credit risk management. As their lending business becomes increasingly more diverse and complex, many large banks respond by introducing more structured and formal credit systems and banks' own internal rating systems are crucial inputs for such systems. Lastly, as for bank regulators, examining bank lending can help them determine regulatory capital reserve requirements and other related policies and assist government's regulations on banks. US regulatory agencies already use internal ratings in their supervision of banks[12]. Under Basel II guidelines, qualified banks are even allowed to use Internal Ratings-Based Approach to calculate their regulatory capital. Thus, it is important to know the nature of the inputs of banks' own rating system.

Where does the information that banks use for their loan decisions come from then? Theory of financial intermediation indicates that in the process of fulfilling their "delegated monitoring" role as a bank, banks collect private information about the borrowers they monitor (Diamond 1984 and Fama 1985).

[12] Rating Credit Risk: Comptroller's Handbook: http://www.occ.gov/publications/publications-by-type/comptrollers-handbook/rcr.pdf.

As stated by Schumpeter, *"… the banker must not only know what the transaction in which he is asked to finance and how it is likely to turn out but he must also know the customer, his business and even his private habits, and get, by frequently 'talking things over with him' a clear picture of the situation…*" (as cited in Diamond 1984, p. 393).

In this paper, following existing literature, this type of *non-quantitative* private information that arises from loan officer's interaction with her corporate clients is called "soft information". More specifically, they are "information which is difficult to completely summarize in a numeric score" (Petersen 2004) and "information that cannot be directly verified by anyone other than the agent who produces it" (Stein 2002). On the other hand, "hard information" refers to *quantitative* information that is publicly available from corporate financial statements and other sources. In summary, both hard information and soft information can be public or private information. However, hard information is quantitative and more comparable, does not need to collected in person, and the collection and use of which can be done by separate people; while soft information is more qualitative and less comparable, needs to collected in person, and the collector and user of which are not separable. Financial statements, history of payment, stock returns are some examples of hard information; while assessment of what's going on in the business, the industry, management's skills, or other characteristics, relationship with the loan officer are examples of soft information.

While the use of hard information is intuitive and well-documented in both the theoretical and empirical literature, there has only been scarce empirical support regarding the use and importance of soft information. In the Banking literature, researchers have long contended that loan officers use *both* hard and soft information when making corporate loan decisions. In theory, the relative importance of hard and soft information should depend on the types of corporate clients (e.g. large versus small, public versus private, etc.), types of loan contracts, accounting practices, and the legal system. However, empirically, because it is challenging to quantify soft information, the actual use and usefulness of soft information in practice still have mixed results and remains unclear.

In this research, I study empirically whether banks indeed *incorporate* soft information of their corporate borrowers when making their commercial loan decisions, and if so, whether this *improves* banks' loan decision making. I seek to answer these two questions in the context of one of the four largest state-owned commercial banks in China (I will call it "the Bank" hereon) with majority of the sample being large, private firms. I use this setting for two reasons. One is that it provides a particularly interesting environment for my tests. When majority of the firms are large companies (i.e. there is ample public information available), is it still necessary and useful to collect and use soft information? The existing literature has established the importance of using relationship information for small firms and consumers on loan underwriting or pricing (e.g., Petersen and Rajan 1994, Berger and Udell 1995, Scott 2004, Uchida, Udell and Yamori 2007, Cerqueiro, Degryse and Ongena 2008, Agarwal et al. 2010 & 2011, and Puri et al. 2012).

The consensus is that a bank's information production makes the most sense where firms are the most opaque, have only restricted access to public securities markets and almost exclusively rely on bank financing and private intermediated markets. What is less obvious and largely unanswered is whether banks collect private information and whether such information matters for large industrial firms that are more transparent.

Secondly, if soft information is used, how effective is it to be used in a bank that is controlled by the government? Especially some of the bank's clients are also completely or partially owned by the government. Berger et al. (2005) explores a bank's ability to act in projects that require the evaluation of soft information and finds that small banks are more capable of collecting and acting on soft information than large banks. I am going to test the collection and use of soft information not only in a large bank setting but rather a state-own large bank.

The main difficulty facing research in this area is that it is challenging to quantify without details of loan contracts, such as the types of corporate clients, types of loan contracts, accounting practices, the legal system, etc. Especially, most of the research lack the necessary time-series data to trace bank's credit evaluation of a loan over time. I am able to provide answer and evidence to these questions because of the proprietary loan database obtained from the Bank. It not only provides the details of loan contracts of all the loans issued by the Bank but also how the Bank's credit status evaluation of a loan changes over time.

Specifically, I have performed two tests. First, I test whether firms' soft information is incorporated into banks' Internal Credit Ratings (ICRs) – the ratings assigned and used by bank personnel when making loan decisions. The ICRs summarize the risk of loss due to failure by a given borrower to pay as promised. Banks' ICRs differ significantly from public agency's ratings, such as Moody's or Standard and Poor's, in architecture and operating design (Treacy 1998), and the process and ratings usually are not revealed to outsiders. Because they are assigned by bank personnel, they can be affected by the bank personnel's personal knowledge of the borrowers.

The first empirical result shows that soft information plays an indispensable role in a bank's ICRs, and banks' loan decision making depends on *both* hard information and soft information. This is consistent with the theoretical literature on financial intermediation. For example, Diamond (1984) examines banks' delegated monitoring role in which bankers incorporate both "hard" and "soft" information into their information production. Stein (2002) first investigates the importance of soft information in borrower-bank relationship by focusing on identifying differences in the use of soft information across different organizational setups. His model shows that a decentralized banking hierarchy is more attractive when a project' soft information is to be evaluated. My result is also consistent with the scarce existing empirical literature directly examining this topic. For example, Liberti (2004) documents a recent trend of hardening of soft information and incorporating it into ICRs. However, Griffin and Tang (2012) suggests that this step would be in the wrong direction by analyzing the parallel phenomenon in CDO credit ratings and showing that recent movement in the CDO market has made rating process more qualitative. So is it a "good idea" to incorporate qualitative/soft information in ICR? This seems to be largely depends on whether the important role of "soft" information in ICRs is a desirable or problematic feature and has been remaining an open question.

This brings out my second test to empirically examine the effectiveness of soft information. In particular, I want to find out whether the inclusion of soft information in ICR leads to a "better" or "worse" prediction of the borrowing firm's future loan default and financial health. My second result provides evidence that soft information has positive contribution to the Bank's prediction of a firm's loan performance and future financial health. Empirically, there are very few research directly examining the effectiveness of soft information in the loan decision process and there has been mixed evidence in the existing literature on this topic.

First, there is evidence that effectiveness of soft information depends on the specific condition under which it is collected and used. Liberti and Mian (2009) find that the efficient use of soft information depends on hierarchical and geographical distance between the agent who collect the information and the one who actually uses it by evaluating a large bank in Argentina. However, their result is based on one point of time and not an evolution of rating changes. Agarwal and Hauswald (2010) confirms that banks do collect soft information on borrowers but banks' ability to collect soft information erodes with distance. Different from my sample of large firms, their research is focused on small, informationally opaque local bank customers.

Secondly, there is evidence on the negative role of soft information. Nakamura and Roszbach (2013) finds out that when too much weight is placed on soft information, or when there is "overconfidence" of loan officers, it leads to an ineffective and inefficient internal credit rating system. Recent work has also shown that screening and monitoring quality by financial intermediaries dropped substantially in the wake of the 2008 financial crisis (Keys et al. 2009).

However, there are also research that has found positive role of soft information. Garcia-Appendini (2011) asks a similar question to mine in the setting for small business and finds that banks do use soft information in making lending decisions and when combining soft and hard information, the power to predict credit outcomes is stronger. Grunert et al. (2005) asks the similar questions by examining 4 major German banks. Similarly, they also find that soft information contributes to ICRs and that use of both hard and soft information lead to a more accurate prediction of future loan default. The major difference between Grunert et al. (2005) and my paper is that I also find that soft information contributes to banks' accurate prediction of firms' future financial distress; and by looking at the ICRs evolution[13], I am able to evaluate

[13] See Figure 3.1 for graphic explanation of examining the evolution of ICRs.

how the impact of soft information on ICRs changes over time since I have a much longer time period - 11 years vs. 5 years, and a much larger sample size – 3,301 firms and 9,737 firm-years vs. 240 firms and 409 firm-years. Chang et al. (2014) is the paper most close to mine. They also uses a proprietary database from a large Chinese state-owned bank. Not only do they find a positive contribution of soft information in predicting future loan defaults but also they find that soft information has a stronger prediction power than hard information in predicting future loan defaults for firms that have a more sustained banking relationship. I engage in similar methods for my tests. However, the biggest difference of my paper and Chang et al. (2014) is that the hard information they use in their model for loan determinants are all "pure" financial statement measures, while I also include an easily quantifiable relationship measure as part of the hard information in my base model and use alternative relationship measures in seven robustness check tests. Even with stronger hard information controls, I still find significant predicting power of soft information on future loan defaults and firms' future financial health.

Despite the importance of analyzing bank lending determinants for both corporate finance and banking, very few studies are available in the extant literature due to data limitation on commercial loan contracts – in both developed and emerging markets. This paper contributes to the relationship banking literature by filling in this gap through empirically examining the role of soft information on bank's internal credit rating and its evolution over time. Furthermore, through ICR, I link soft information to the outcome of future loan performance and firms' financial health.

The rest of the paper is organized as follows. Section 2 provides details of the data source, variable definition and summary statistics. Section 3 provides the details of the two main tests and their results. Section 4 discuss additional tests and their results. Section 5 concludes.

3.2 Sample Construction

The sample is composed of three datasets. The first one is a *proprietary commercial loan database* provided by one of the largest state-owned commercial banks ("the Bank") in China. As can be seen in Table 3.1, the Bank issued around $334 billion corporate loans in a random year in the 2000s, which accounted for about 16% of the corporate lending in the entire Chinese domestic banking market. The loan database contains detailed information on all corporate loans extended by the Bank during the period of 1999 to 2009 in five municipalities or provinces (Beijing, Liaoning, Guangdong, Shanghai, and Zhejiang). For each loan transaction, the database provides the identity of the borrower, the loan amount, the interest rate, the maturity, the collateral used to secure the loan, the proposed use of the loan, the change of credit status (evaluated by the Bank) over the life of the loan (the evolution of the Bank's ICRs), the complete repayment history of the loan by the borrower, and other items. To my knowledge, this is the most comprehensive loan database made available for academic research, including those that cover the US market.

The other two data sets are on firms accounting information. One is provided by the Bank, being retrieved from the Bank's own backup accounting files used in its loan assessment process; and the other one is purchased from a Chinese data vendor SinoFin Financial Information Service. The SinoFin database provides annual financial statements for more than 200,000 Chinese companies (listed and non-listed) with annual sales greater than RMB 5,000,000 (approximately US $700,000 at the exchange rates of 2011) from 1999 to 2007. In addition, it provides detailed corporate information including nature of business, legal and ownership structure, etc. The primary source of SinoFin data is the National Bureau of Statistics – the only official Chinese government agency that compiles statistical data. This is one of the most comprehensive and reliable data source for accounting information on Chinese companies. I build the firms' accounting database by combining the information from the two accounting datasets which have both overlaps of firms and unique coverage not included in the other dataset. When overlaps occur, I have conducted the tests by using only the Bank's data (for my baseline test), only SinoFin's data, or an annual average of the same firm from both datasets (for my robustness tests).

Since both the Bank's loan database and backup accounting file use the same unique identifier for each company, connecting these two datasets only requires matching the company identifier. However, connecting the Bank's loan dataset and SinoFin's accounting dataset require manual Chinese name matching. These two datasets use completely different identifying system and there are different versions for the same companies' Chinese names – with characters positioned in different order, or with additional characters, or blank spaces placed at different spots in the name. Therefore, matching method is based on keywords matching in the company name, supplemented by other firm characteristics, such as company location, industry, phone number, firm size, and manual double checking.

By combining the proprietary loan database with corporations' accounting and market data, I am able to evaluate the role of soft information in bank's loan decision making. In this paper, I report the results from one of the five branches - Beijing[14] branch from 1999-2009. All loans are based on location-dependent lending, which means all borrowers are located locally as the Bank branch in Beijing. The main variables used include identity of the borrower, the loan amount, the interest rate, the maturity, the collateral used to secure the loan, proposed use of loan money, ICRs over the life of the loan, and complete repayment history of the loan by the borrower. Table 3.2 shows the summary statistics of the resulting sample.

[14] The original data set has loan data in 5 branches. The other data will be used in future work.

3.3 Methodology

The Bank uses a Five-Class Internal Credit Rating (ICR) system for its loan evaluation, with 1 as the highest quality and 5 as the lowest. Rating 1 means “good”, while 2 “Questionable”, and 3-5 mean “problematic”, “loss”, and “big loss” respectively indicating there are certain deterioration in hard information already. In the following tests, I will focus on rating 2 because based on the detailed definitions of the Five-Class ICR (see Table 3.3), this is likely the time when soft information plays the most important role. It is also the time when loan officers seem to have a substantial subjective judgmental role.

I also decide to convert all the loan-level ratings to annual firm-level ratings and use the latter in the tests. First of all, because the same firm can have different loans with different loan terms in the same year, it can have different loan-level ratings in the same year. Thus, the difference of the loan-level ratings may not necessarily be due to the firm-level information but rather the loan-level information. By aggregating the loan-level ratings for the same firm each year, I can minimize the noise caused by the loan level information. Secondly, converting to firm-ratings at annual frequency can also help me to match the frequency of the accounting data. For example, suppose that we have two loans -- one collateralized and the other one not. If the underlying hard information is similar, the first loan may get a rating 1 but the second one may get a rating 2. This will add noise to loans with assigned rating of 1 and thus make it more difficult to find significant relationship between hard information and credit ratings. On the other hand, if the loan-level ratings are aggregated to the firm-level and I observe a firm-level rating of 2 for any of the outstanding loans granted to a firm, then there must be some concerns about the financial health of the firm.

Following are the procedures I take to assign the firm ratings.

1) First, use the rating of the loan with the largest balance at the beginning of the year; if there are several loans with the same largest balance, then
2) Use the rating that has the maximum number of loans in the year; if there are several ratings with the same maximum number of loans, then
3) Use the rating that has the maximum total balance in the year; if the rating is still not unique then
4) Use the rating of the loan with the earliest loan initiation date.
5) Finally, keep ratings 1 and 2 and assign missing to all other ratings.

This results firm-level ratings being 1 or 2 or missing. Whenever a firm-level rating is missing, it indicates that the firm’s loan is in default status. Additionally, all the tests are conditional on that a firm has been granted a loan because my database does not include information on rejected loan applications. I windsorize all firm characteristic variables used in the tests in order to remove extreme values. I then take the following four steps to answer the research question.

3.3.1. Step 0: Pretest

First, I perform a test to make sure the ICR system works the way it should. If it does, we should expect that a loan with a better rating this year to perform better next year (compared to a worse rating) and thus predict a lower probability of loan default and firm financial distress next year, and vice versa.

I create two dummy variables *LD* (Loan Default) and *FD* (Financial Distress). Based on the loan rating definitions and their corresponding probability of default (as shown in Table 3.3), LD takes the value of 1 when ICR is in 3-5. Otherwise, LD takes the value of 0. The reason why I define loan default this way is because by the Bank's internal standard, a rating of 3, 4, or 5 means a bad loan. After a loan turns bad, the Bank may be engaged in renegotiation with the borrower and this may delay the actual loan defaults recorded by the bank but in fact the loan is already a bad loan.

$$LD_t = 1, \qquad when\ ICR_t = (3,4,5)$$
$$LD_t = 0, \qquad Otherwise$$

A firm is in financial distress when it has difficulty paying off its financial obligations to its creditors. Thus *FD* is defined as the following:

$$FD_t = 0, when\ \ EBIT_{(End-of-Year)t}/Interest\ Payment_{(Entire\ Year)t} \geq 1$$
$$FD_t = 1, \qquad Otherwise$$

I test whether rating 2 (i.e. a worse rating) has a stronger predictive power for LD=1 (loan default) and FD=1 (financial distress) than rating 1 (i.e. a better rating). I expect to see that loans with rating 2 this year predict next year's loan default and firm financial distress with a higher probability than those with rating 1. Thus, I design the pretest as the following probit regressions:

$$P(LD_t) = R2_{t-1} + a_{t-1} + b_i \quad (1)$$
$$P(FD_t) = R2_{t-1} + a_{t-1} + b_i \quad (2)$$

Here, a_{t-1} and b_i are time and industry fixed effects, and *R2, LD*, and *FD* are all dummy variables. *R2* stands for rating 2 and takes the value of 1 when firm rating is 2 and 0 when firm rating is 1. *LD* and *FD* stands for loan default and financial distress respectively and are defined as above.

The result (as in Table 3.3) shows that a worse rating (rating 2) *does* predict loan default and firm's financial distress with a higher probability than a better rating (rating 1) in the following year and the difference is statistically significant at 1% level. This means the current ICR system does work the way it is design for. Next, I am going to explore the inputs to the ICR system and see if it includes the soft information.

3.3.2. Step1: Test 1

First, I want to verify that hard information does contribute to the ICR system. The test is specified as the following probit regression:

$$P(R2_t) = X_{t-1} + a_{t-1} + b_i \qquad (3)$$

Here I test the probability of getting loan rating of 2 versus 1. The reason why I want to compare rating 2 with rating 1 is because I think rating 2 is when the loan officer can exercise the most subjective judgment in the loan decision making process. As shown in Table 3.3, ICR 1 are considered "good" loans, ICR 3-5 are considered "bad" loans, while ICR 2 is the transitional and the most unstable rating and thus is when soft information plays the most important role. As the definition for rating 2 says, when rating 2 is given, it means "…there ***exist*** factors that ***may*** have negative impact on the borrower's ability to repay the loan." I suspect that loan officers need to use substantial judgment when deciding whether the quality of a loan has improved, declined or remained the same when assigning rating 2 to it.

Here for equation (3), again the dependent variable *R2* equals to 1 when firm rating takes the value of 2, and equals to 0 when firm rating takes the value of 1, and a_{t-1} and b_i are time and industry fixed effects. Here, X_{t-1} represents firm's hard information. I include an extensive set of variables for the hard information. Specifically, I include *size* which is the log value of firm's total assets. Next, I include *Z-score* which is a linear combination of four or five common business ratios on firms' liquidity (T1), profitability (T2 and T5), productivity (T3), and leverage (T4), weighed by coefficients, for predicting firms' future bankruptcy. It was first published by Edward I. Altman in 1968 and thus also called Altman's Z-score. I use two versions of Altman's Z-score in the baseline model and robustness check model respectively: *Z-score1* is Altman's Z-score estimated for US private firms (Altman 2000), and *Z-score2* is Altman's China Z-score for listed firms (Altman et al. 2007). My sample is composed of large Chinese firms and are composed of both listed and non-listed firms (with majority as unlisted firms), so both Z-scores are close approximations for my needs and give similar results. Following are details of the calculation and definitions of the two Z-scores.

$$Z-score1^{15} = 0.717 * \mathrm{T1} + 0.847 * \mathrm{T2} + 3.107 * \mathrm{T3} + 0.420 * \mathrm{T4} + 0.998 * \mathrm{T5}$$

$$Z-score2^{16} = 0.517 + 0.388 * \mathrm{T1} + 1.158 * \mathrm{T2} + 9.320 * \mathrm{T3} - 0.460 * \mathrm{T4\_1}$$

[15] Altman's Z-score estimated for US private firms (Altman 2000)
[16] Altman China Z-score - listed firms (Altman et al. 2007)

T1 = (Current Assets-Current Liabilities) / Total Assets = Working Capital/Total Assets (Liquidity measure)

T2 = Retained Earnings / Total Assets (Profitability measure)

T3 = EBIT / Total Assets (Productivity measure)

T4 = Book Value of Equity / Total Liabilities (Leverage measure)

T5 = Sales/ Total Assets – capital turnover ratio (TurnOver: Profitability measure)

T4_1=total liability / total assets (Leverage measure - reciprocal of T4)

I then included a group of dummy variables: *FD*[17] takes the value of 1 when firm is in financial distress and 0 otherwise; *ld_io* takes the value 1 when firm has loan default[18] or interest overdue[19] in the year and 0 otherwise; *state_own* takes the value of 1 when a firm is state owned and 0 otherwise; *emphasis* takes the value of 1 when the Bank regards the customer as important to it and 0 otherwise[20]. Finally, I include four relationship measures and four corresponding dummies with the first being used in my base model and the rest in robustness check models. The relationship measures include log of length of bank and firm relationship (in number of years), log of number of loans (that have been issued from the Bank to the firm), log of average loan size (for all the loans that have been issued from the Bank to the firm), log of total loan size (for all the loans that have been issued from the Bank to the firm), whether the previous business relationship between the Bank and firm measured in years is at least at the mean sample level (dummy), whether the number of loans that have been issued from the Bank to the firm is at least at the mean sample level (dummy), whether the average loan amount is at least at the mean sample level (dummy), and lastly whether the total loan amount is at least at the mean sample level (dummy). All explanatory variables are measured in the year before (lag value), unless stated otherwise. Detailed definition and calculations of the variables are included in Table 3.15.

I present the result of the baseline model in Table 3.5 column 1. My results verified that hard information is indeed important in determining ICRs. In particular, size, z-score, firms' past financial distress, and past relationship with the bank all significantly impact firms' probability of getting loan rating of 2 versus 1. In particular, when a firm's size is small, financial health is poor and has past occurrence of financial default, there is a higher probability of it getting a rating 2 vs. 1. When a firm has a longer relationship with the bank, it is also more likely to get a rating of 2 vs. 1. This can be understood as the following. When a firm has a long relationship with the bank, bank would be able to collect more soft

[17] Definition of FD is the same as in Section 3.3.1.
[18] Loan default is defined as when firms' ICR takes the value of 3, 4, or 5, the same as in Section 3.3.1.
[19] Interest overdue information is obtained from an interest overdue flag from the loan database.
[20] This value is taken directly from the variable "emphasis flag" from the loan database which is an indicator of the importance of the customer to the bank.

information on the firm, thus be more informative with the inner works of the firm and more sensitive with any negative indicator of the firm. I also notice that emphasis flag doesn't show statistical significance. This can be interpreted as that past credit payment does not seem to be important when soft information is considered which is consistent with findings in Garcia-Appendini (2011).

I further conduct robustness checks and present the results in Table 3.5 columns 2-11. Here, I use several alternative z-score measures to replace z-score1 (i.e. z-score2 and average of 1-year and 2-year lag values for both z-scores[21]) and use alternative measures for lender-borrower relationship. Firm size, z-score and financial distress indicator continue to show similar magnitude and statistical significant as in the base model (model 1), while bank-firm relationship measures vary.

I also find some suggestive results regarding state ownership. State ownership does not show a consistent sign. For example, in model 5, when I use the average amount of loans as the relationship measure, the state ownership variable is significantly positive, which means that when a firm is state owned, there is a higher probability that it is going to get a rating 2 versus 1. However, the state ownership variable loses its significance in model 1, when we measure the past relationship with the number of bank-firm years. This could mean that compared with average loan amount, number of years is a much stronger measure of lender-borrower relationship. When number of years enter the test, it dominates the relationship. The longer the relationship, the more internal information the loan officer gathers about the firm and the more sensitive the loan officer becomes to the negative information of the firm, which lead to a higher probability for the firm to get a lower rating. I also notice that, in model 5, when only average amount loan enters the test as the relationship measure, it gives us a significant negative sign. This shows that compared to a non-state owned firm which has a larger average loan size from the Bank, a state-owned firm with a smaller average loan amount will have a higher probability of getting the worse rating 2 versus the better rating 1.

Z-score is a comprehensive measure of a firm's general health. If I break it down to its five components, namely the liquidity, profitability, productivity, leverage (reciprocal of leverage) and profitability measures (T1-T5) and rerun the models above, I should be able to see how each component in the z-score is impacting the probability of firm receiving loan rating 2 versus 1. As shown in Table 3.6, these further robustness checks show similar results for firm size and past financial distress as in Table 3.5. However, now I am able to "peek inside" the z-scores. I find that when a firm's productivity (T3) is lower and leverage (T4) is higher, there is a higher probability of firm getting a loan rating of 2 verses 1 and the results are statistically significant.

[21] Refer to definition and calculation in Table 3.15.

3.3.3. Step2: Test 2

Next, I want to find evidence on whether soft information is included in ICR.

In this step, I match firms with rating 1 and those with rating 2 based on firm characteristics as identified in Section 3.3.2 Test 1. First, I calculate rating 1 and rating 2 firms' Propensity Scores (PS) by using the following probit model.

$$P(rating_{t-1}) = size_{t-1} + Zscore_{t-1} + FD_{t-1} + LD\_IO_{t-1} + state\_Own_{t-1} + emphasis_{t-1} + num\_years_{pre} + a_t + b_i \qquad (4)$$

Then, I create matching pairs of rating 1 and rating 2 firms based on the same year, the same industry (based on SIC code) and similar propensity scores (within 10% of PS without replacement) and end up with 3643 pairs of matched firms. As can be seen in Table 3.7, the two groups' PS are very similar with the mean difference being 3 basis points and maximum difference being 183 basis points. Table 3.8 shows the summary statistics of key characteristics of these two groups of firms. Again, these two groups look very similar in all these main firm characteristics that I consider as key inputs for the Bank's ICR hard information.

In order to address the concern of the bias generated by unobservable confounding factors, I have used the following approaches. For the basic PS matching as stated above, I use an extensive list of hard information variables based on the literature in order to reduce as much bias as possible. In addition, I use different matching methods for robustness checks and get similar results:

1) I match rating 1 and rating 2 firms with PS above the mean only and end up with 2078 matched pairs;
2) I match firms on same year, same industry, and similar lag 1 year Z-scores;
3) I match firms on year, industry and other models of PS (using different z-scores and different relationship measures to replace num_years).

   Both 2) and 3) also lead to substantial set of matched firms.

This naturally raises a question – why would these two *matched* group of firms with *very similar* firm financial characteristics get assigned *different* ratings? This suggests that the Bank must have incorporated factors other than the available hard information in their ratings. I consider this as strong evidence of the Bank incorporating soft information in its ICR system.

3.3.4. Step3: Test 3

Now that I have found evidence showing that soft information is used in ICR, in this test, I want to examine the usefulness of soft information as used in the ICR system. In particular, I will explore whether the addition of soft information leads to a “better” or “worse” evaluation of future loan performance and firms’ financial health by examining how previous ratings (2 vs. 1) predict future loan default (i.e. ICR being 3, 4 or 5) and financial distress (EBIT/Interest <1).

On the one hand, I expect the use of soft information by the Bank to improve the information content of the internal credit rating, relative to what can be gauged from hard information alone. Thus, if the internal rating is sensible, I would expect the internal credit rating to do better than publicly available measures in predicting ultimate loan performance and see a stronger prediction power of loan default and financial distress if the previous rating is 2 vs. 1. However, on the other hand, because the Bank is controlled by the government, political influence and bureaucracy can potentially distort the hard to be quantified information component in the rating system.

I use the matched sample from test 2 to run the following two probit regressions: probability of future loan default on firms’ ratings and probability of future firm financial distress on firms’ ratings.

$$P(LD_{t+1}) = R2_t + a_t + b_i \qquad (5)$$
$$P(FD_{t+1}) = R2_t + a_t + b_i \qquad (6)$$

Here, definitions of *R2*, *LD* and *FD* are all the same as in Section 3.3.1 and 3.3.2.

The result, as presented in Table 3.9, shows that for either the matched PS sample or the above-mean PS matched sample, rating 2 has a statistically significant higher predicting power than rating 1 in predicting future loan default and firm’s future financial distress. Specifically, for the baseline model (by using the matched sample), I find that when loan rating changes from 1 to 2, probability of loan default increases by 73% and probability of financial distress increases by 61%. For the robustness check, using the smaller set of above-mean matched sample, my result still shows that when loan rating changes from 1 to 2, probability of loan default increases by 64% and probability of financial distress increases by 59%. This demonstrates that despite the government’s influence, the big Chinese bank has a very efficient loan evaluation system!

In summary, soft information has proven to be a useful component in ICR. It helps improve the prediction of future loan default by 64% - 73% and helps improve prediction of firms’ future financial distress by 59% - 61% when compared with using hard information alone.

3.4 Additional Tests and Robustness Checks

In 2005, there was an important reform in the Bank which lead to a revolutionary change in its ICR system. Following I am going to test the impact of this reform on the Bank's ICR system.

3.4.1. Rollover Test

In the following test, I look at both Beijing and Guangdong branches and test whether 2005 reform leads to any changes in the rating outcomes. In the dataset, there is a special loan indicator for rollover loans. As shown in the descriptive statistics of these two samples in Table 3.10, the percentage of rollover loans that defaulted or firms that become financially distressed are much lower for post-2005 period compared with the pre-2005 period.

Following the probit regression model in (7), I test whether the Bank changes its criteria in granting rollover loans after the reform.

$$P(Rollover_t) = X'_{t-1} + a_{t-1} + b_i \qquad (7)$$

The result, as presented in Table 3.11, show that in general, it is less likely to get rollover loans after 2005. The characteristics of firms that received "rollover" loans also changed over time. Firms with lower profit are more likely to receive rollover loans in the post-2005 period. Firms that have past financial distress, lower leverage, lower capital turnover (for Beijing sample) or lower productivity (for Guangdong sample) are more likely to get rollover loans and these characteristics do not significantly change before and after the 2005 reform.

While the other factors are intuitive, why would firms that have experienced past financial distress and lower profit have a higher probability of rolling over their loans? I suspect the reason could be that the ratings after the reform were artificially inflated. The Bank may have intentionally used rollover loans to reduce the loan default rates.

3.4.2. Revised Test 1

Similar to Section 3.3.2 Test 1, following model (8), I run probit regression to test the likelihood getting rating 2 vs. 1 on firms' hard information in two time periods - before 2005 and after 2005 in order to test whether there is any change in the prediction power of hard information on ICRs before and after the reform. However, this time, I use the propensity matching sample for the test. Other than the original PS matching sample without replacement, I also create a PS matching sample with replacement. The hard information includes size, FD, and five breakdown components of Z-score1.

$$P(R2_t) = X'_{t-1} + a_{t-1} + b_i \qquad (8)$$

The results are presented in Table 3.12. For the Beijing sample of post-2005 period, consistent with my earlier result, when firm has small size, has past occurrence of financial default, has a low productivity and high leverage, there is a higher probability of it getting a loan rating of 2 verses 1 and the results are statistically significant. However, the pre-2005 period sample shows no statistical significance on past occurrence of financial default. It appears that 2005 reform has improved the prediction power and accuracy of hard information for the Beijing branch.

The Guandong branch has similar result for the post-2005 sample as Beijing. Except for Guangdong, higher capital turnover and higher productivity factors can also increase the probability of getting rating 2 vs. 1. This could be because these two factors can be associated with a smaller firm and smaller firms have a higher probability of getting rating 2 vs. 1. Guangdong sample does have a consistent prediction power from past financial distress for both the pre-2005 and post-2005 sample. In my future research, I will conduct test to find out whether this difference is due to the different political environment in Guangdong and Beijing. In another word, I suspect that Guandong provides an environment with less political influence on both the Bank and firms and thus Guangdong branch's ICRs have less noise than Beijing's which were contaminated because of the political environment until after the 2005 reform.

As a robustness test, I run the same test only on firms in the biggest industry in my sample – manufacturing industry. Results are similar and are presented in Table 3.13.

3.4.3. Revised Test 3

Now that we know the rating system appears to have improved after 2005 reform, I will continue the tests on the prediction of soft information on future loan default and finance distress by following model (9) and (10). I conduct this test on Beijing sample with different specifications of the model and present the results in Table 3.14.

$$P(LD_{t+1}) = R2_t + R2_t * post_t + a_t + b_i \qquad (9)$$
$$P(FD_{t+1}) = R2_t + R2_t * post_t + a_t + b_i \qquad (10)$$

Here *post* takes the value of 1 if time is after 2005 and 0 if it is before 2005. The coefficient I am most interested in is $R2_t * post$. The results indicate that, in general, the ICRs' prediction power for future loan default increased significantly after 2005 but the impact on financial distress is unclear.

In summary, it seems that 2005 reform has improved the Bank's ICR system. However, when combining the rollover results and the fact that only the prediction power of loan default has improved and not financial distress, which is a cleaner and less manipulative measure of a firm's health, this seemingly improvement could be man-made. More tests need to be done in order to find out the true effect of the reform.

3.5 Analysis and Conclusion

My test results show that soft information has real impact on banks' loan decision making. ICRs depends on *both* hard information and soft information. Soft information plays an indispensable role in a bank's ICRs. In order to understand ICR, we must understand the use of soft information. Soft information or hardening of soft information should be a factor to consider in determining bank regulations. Furthermore, as an integral component of ICR, soft information not only helps to predict future loan default and but also a firm's financial distress. This study verifies the *positive* role of soft information in credit evaluation.

In future work, I will continue the work on soft information's real pricing impact by looking at specific loan terms. For example, I will focus on a subset of firms that have history of past financial distress and examine when their financial situation improves, whether their ICRs get upgraded. If it is the case, whether this lead to a real change in loan terms. Theoretically, this can go either way which leaves it to be an interesting empirical question. My hypotheses are: a) banks do not have incentives to improve loan terms for the firms. Thus, they will only downgrade an ICR instead of upgrading it; and b) banks will improve loan terms for the firms due to the consideration of long-term relationship or cross-selling.

I will also further enjoy the richness of the dataset by looking at bank branches in other provinces to explore the differences under different political environment.

I may also investigate the role of political connections on bank decisions. Political connections are likely to be especially important in countries where investor protection and corporate governance are weak. The banking industry in China provides an ideal environment to examine this issue, due to the historical influence of the government on bank's lending practices and the slow pace of reform in the banking industry.

3.6 Tables and Figures

Figure 3.1 The Bank's ICR Evolution

This figure depicts that a loan is ininiated at time T1 and is assigned an initial rating ICR_0 with both hard and soft information as input. Then at some point of time T2, or at multiple times before loan matures (T2, …) , the Bank may re-evaluate the firm's credit and adjust its rating to ICR_1, (ICR_2,…), again with hard and soft informaiton as input. At time TM, loan matures with an ending rating ICR_M. By examining the ICR evolution over time, I mean examiming ICR_0, ICR_1, ICR_2,… ICR_M.

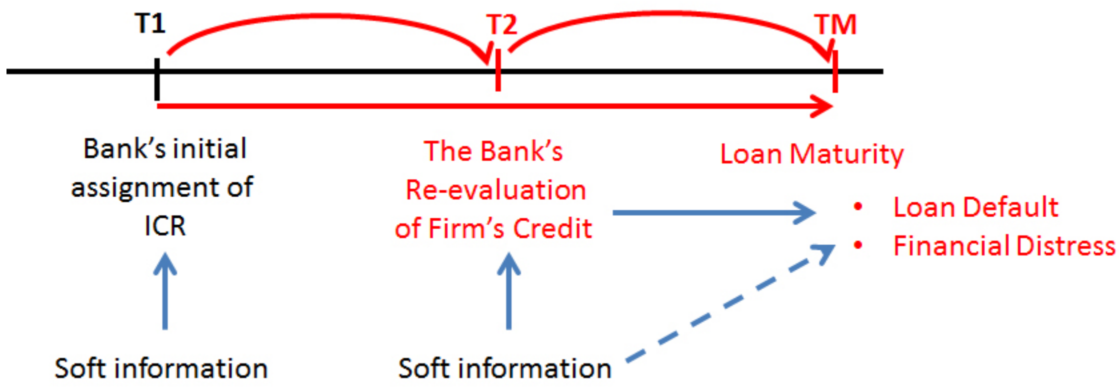


Table 3.1 Key Financial Variables of "the Bank"

Note: Due to confidentiality, the identity of the Bank cannot be released. Thus here I only report selected financial variables for *a random year* vs. a specific year. *Market refers to domestic banking market.

	A random year after 2000	Market Share* (%)
Deposits ($billion)	693.1	20
Corporate deposits ($billion)	317.7	23
Savings deposits ($billion)	375.5	22
Loans ($billion)	397.5	17
Corporate loans ($billion)	333.7	16
Personal loans ($billion)	63.7	24
Total assets ($billion)	780.0	17
# corporate customers (million)	2.5	
# individual loan customers(million)	3.93	

Table 3.2 Descriptive Statistics of the Sample

Note: This table reports the mean value of firm-specific variables over the sample period of 1999-2009.

Panel A: Main Characteristics of the Sample

Variables	Values	Unit
Num customer_years	9,737	
Num customers	3,301	
Num loans	41,520	
Num contract	39,010	
Average monthly repayment	0.02	(in billion RMB)
Total loan amount	3,273.43	(in billion RMB)
Average loan amount	0.08	(in m RMB)
Average contact maturity	11.01	(in months)
Average actual maturity	8.85	(in months)
Average ROA	0.07	
Average size	61.37	(in m RMB)
Average long-term leverage	0.07	
Average total leverage	0.66	
Average EBIT	2.54	(in m RMB)

Panel B: Industry Composition of the Sample

Industry	Number of firms	percentage of firms
manufacturing	2165	38.2%
real estate	485	8.6%
farming, forestry, animal husbandry and fishery	52	0.9%
architecture/construction	130	2.3%
transportation and shipping industry	141	2.5%
wholesale and retail industry	1635	28.9%
lodging, food and beverage industry	147	2.6%
other	906	16.0%
total	5661	

Table 3.3 Five-Class Internal Credit Rating (ICR)

This table reports the detailed definition of the ICR used by the Bank.

Rating	Definition	Probability of Default
1	**Good**	0
	Borrower has the ability to follow the contract; No sufficient reason to suspect that the loan cannot be repaid on time and in full amount.	
2	**Questionable / Watch**	>0
	Although the borrower currently has the ability to pay the principle + interest in full amount, there ***EXIST*** factors that may have negative impact on the borrower's ability to repay the loan.	
3	**Problematic**	20%
	Borrower *CANNOT REPAY* principle + interest *JUST* based on the firm's normal operating income. Even if there is collateral, there is a still a ***HIGH PROBABILITY OF LOSS*** to the Bank.	
4	**Loss**	50%
	Borrower *CANNOT REPAY* principle + interest. Even if there is collateral, the Bank is ***CERTAIN*** to incur a ***RELATIVELY BIG LOSS***.	
5	**Big Loss**	80%
	After the Bank resorts to all possible measures and legal procedures, borrower still *CANNOT REPAY* principle + interest, or only a very small portion can be repaid - ***BIG LOSS***.	

Table 3.4 Pretest: Probit Regressions for the Likelihood of Loan Default and Financial Distress

This table shows marginal effects of probit regressions predicting the likelihood of a firm having a loan default or financial distress. The dependent variable in column (1) is one if a firm has a loan default for that year and zero otherwise. It follows the model: $P(LD_t) = R2_{t-1} + a_{t-1} + b_i$. The dependent variable in column (2) is one if a firm experience financial distress for that year and zero otherwise. It follows the model: $P(FD_t) = R2_{t-1} + a_{t-1} + b_i$. a_{t-1} and b_i are time and industry fixed effects; and *R2*, *LD*, and *FD* are all dummy variables. *R2* stands for rating 2, and *R2* =1 when ICR = 2, and *R2* = 0 when ICR = 1. *LD* stands for loan default, and *LD* = 1 when ICR = (3, 4 or 5), and *LD* = 0 when ICR = (1 or 2). *FD* stands for financial distress and it is calculated as $FD_t = 0, when\ EBIT_{(End-of-Year)t}/Interest\ Payment_{(Entire\ Year)t} \geq 1$; and $FD_t = 1,\ Otherwise$. Tests are done with both year and industry fixed effects. The intercepts are not reported. Robustness standard errors are clustered at the customer level and reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
	LD_t	FD_t
$R2_{t-1}$	0.4506***	0.3627***
(2 vs.1)	(0.0449)	(0.0451)
Year FE	Yes	Yes
Industry FE	Yes	Yes
# of rating1s	962	1046
# of rating 0s	5538	5454
# of firm-years	6500	6500
# of firms	2115	2115

Table 3.5 Test 1: Probit Regressions for the Likelihood of Getting Loan Rating of 2 vs. 1

This table shows marginal effects of probit regressions predicting the likelihood of a firm getting loan rating of 2 versus 1. The dependent variable is one if the firm's ICR takes the value of 2, and takes the value zero if the firm's ICR takes the value of 1. It follows the model: $P(R2_t) = X_{t-1} + a_{t-1} + b_i$. a_{t-1} and b_i are time and industry fixed effects, and X_{t-1} represents firm's hard information, the definition of which is in Table 1.5. *t*-statistics are in parentheses. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
lsize	-0.2394***	-0.2441***	-0.2795***	-0.2598***	-0.1863***	-0.217***	-0.3657***	-0.2473***	-0.2249***	-0.2362***	-0.2243***
	(0.0174)	(0.0171)	(0.0181)	(0.0176)	(0.0255)	(0.0201)	(0.0266)	(0.0185)	(0.0174)	(0.0172)	(0.0173)
lzscore1	-0.0815***	-0.087***	-0.0905***	-0.0944***	-0.0967***	-0.0967***	-0.0944***	-0.0967***			
	(0.02)	(0.0188)	(0.0209)	(0.0196)	(0.0195)	(0.0194)	(0.0203)	(0.0196)			
lzscore2									-0.1337***		
									(0.0303)		
lzscore1 ave										-0.0855***	
										(0.0184)	
lzscore2 ave											-0.1387***
											(0.0325)
lfd	0.3423***	0.3564***	0.3193***	0.3515***	0.387***	0.3782***	0.3138***	0.3704***	0.3444***	0.3446***	0.3422***
	(0.0575)	(0.0571)	(0.0573)	(0.0568)	(0.0571)	(0.057)	(0.057)	(0.0568)	(0.057)	(0.0573)	(0.0571)
lld lio	0.1016*	-0.00359	0.0462	-0.0056	-0.0051	-0.0046	0.012	-0.012	0.1112*	0.1038*	0.1146*
	(0.0596)	(0.0591)	(0.0554)	(0.0579)	(0.059)	(0.0592)	(0.0569)	(0.0587)	(0.0597)	(0.0595)	(0.0595)
lstate own2	0.0563	0.1288**	0.0794	0.1542***	0.1586***	0.1775***	0.158***	0.1734***	0.0438	0.0559	0.0442
	(0.0588)	(0.0574)	(0.0589)	(0.057)	(0.057)	(0.0566)	(0.0571)	(0.0567)	(0.0592)	(0.0585)	(0.0589)
lemphasis	-0.0246	0.0219	-0.0559	0.0073	0.0618	0.0537	-0.0355	0.0418	-0.0353	-0.0351	-0.041
	(0.0846)	(0.0833)	(0.0865)	(0.0844)	(0.0829)	(0.0826)	(0.0851)	(0.0826)	(0.085)	(0.0838)	(0.0843)
num years pre	0.4596***								0.469***	0.4615***	0.4701***
	(0.0421)								(0.043)	(0.0419)	(0.0425)
num years dummy		0.4464***									
		(0.0635)									
num loans pre			0.2906***								
			(0.0319)								
num loans dummy				0.3284***							
				(0.0664)							
ave loan pre					-0.0859***						
					(0.0331)						
ave loan dummy						-0.161*					
						(0.0883)					
total loan pre							0.1698***				
							(0.0269)				
total loan dummy								0.0909			
								(0.0852)			
N	6377	6377	6377	6377	6377	6377	6377	6377	6378	6414	6414
N-cluster	1785	1785	1785	1785	1785	1785	1785	1785	1785	1790	1790

Table 3.6 Robustness check for Step 1: Test 1 (Probability of getting loan rating of 2 vs. 1)

This table shows marginal effects of probit regressions predicting the likelihood of a firm getting loan rating of 2 versus 1. The dependent variable is one if the firm's ICR takes the value of 2, and takes the value zero if the firm's ICR takes the value of 1. It follows the model: $P(R2_t) = X_{t-1} + a_{t-1} + b_i$. a_{t-1} and b_i are time and industry fixed effects, and X_{t-1} represents firm's hard information, the definition of which is in Table 3.15. *t*-statistics are in parentheses. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
lsize	-0.2335***	-0.1774***	-0.2293***	-0.1804***	lsize	-0.2329***	-0.1778***	-0.2284***	-0.1781***
	(0.018)	(0.026)	(0.0176)	(0.0264)		(0.0178)	(0.0256)	(0.0175)	(0.026)
lT1	-0.0421	-0.0674	-0.1216	-0.183*	lT1_ave	-0.1092	-0.1287	-0.1976*	-0.258**
	(0.1042)	(0.1055)	(0.1051)	(0.1039)		(0.115)	(0.1154)	(0.1179)	(0.1152)
lT2	-0.0278	0.0037	-0.0945	-0.0849	lT2_ave	0.1307	0.149	0.0673	0.0594
	(0.15)	(0.1452)	(0.1478)	(0.145)		(0.1461)	(0.1442)	(0.1491)	(0.1487)
lT3	-1.3945***	-1.602***	-1.5915***	-1.8736***	lT3_ave	-1.7147***	-1.9543***	-1.9272***	-2.2309***
	(0.3845)	(0.3935)	(0.3783)	(0.3814)		(0.4760)	(0.488)	(0.4573)	(0.4683)
lT4	-0.0462**	-0.056***			lT4_ave	-0.0551***	-0.0682***		
	(0.0191)	(0.0199)				(0.0184)	(0.0188)		
lT5	-0.0351	-0.0424*			lT5_ave	-0.0387	-0.0482*		
	(0.0239)	(0.0232)				(0.0272)	(0.0266)		
lT4_1			-0.0505	-0.0918*	lT4_1_ave			-0.024	-0.0675
			(0.0488)	(0.0527)				(0.0782)	(0.0795)
lfd	0.3397***	0.3849***	0.3379***	0.3787***	lfd	0.3364***	0.3804***	0.3357***	0.3769***
	(0.0575)	(0.057)	(0.0573)	(0.0568)		(0.0576)	(0.0575)	(0.0572)	(0.0568)
lld_lio	0.1011*	-0.0048	0.1084*	0.0026	lld_lio	0.0994*	-0.006	0.1116*	0.0061
	(0.0598)	(0.0591)	(0.06)	(0.059)		(0.0596)	(0.0588)	(0.0595)	(0.0587)
lstate_own2	0.0358	0.1318**	0.0353	0.1333**	lstate_own2	0.0272	0.1241**	0.0266	0.1271**
	(0.0592)	(0.0576)	(0.059)	(0.0573)		(0.059)	(0.0573)	(0.0589)	(0.0572)
lemphasis	-0.0328	0.0509	-0.0309	0.0522	lemphasis	-0.0438	0.0363	-0.041	0.0402
	(0.085)	(0.0834)	(0.0856)	(0.084)		(0.0844)	(0.083)	(0.0849)	(0.0834)
num_years_pre	0.4544***		0.4575***		num_years_pre	0.4535***		0.4611***	
	(0.0424)		(0.0426)			(0.042)		(0.0423)	
ave_loan_pre		-0.0898***		-0.0774**	ave_loan_pre		-0.088***		-0.0792**
		(0.033)		(0.0337)			(0.033)		(0.033)
N	6377	6377	6378	6378		6414	6414	6414	6414
N-cluster	1785	1785	1785	1785		1790	1790	1790	1790

Table 3.7 Step 2: Summary Statistics of Propensity Score Distribution of the Matching Sample

	N	Mean	Median	Std Dev	min	25%	75%	90%	max
ps_rating2	3643	0.6598	0.6916	0.1742	0.006	0.557	0.7907	0.8589	0.9852
ps_rating1	3643	0.6598	0.6916	0.1741	0.0061	0.557	0.7906	0.8590	0.9669
ps_diff	3643	0.0003	0.0001	0.0007	0	0	0.0003	0.0005	0.0183

Table 3.8 Step 2: Summary Statistics of the Matched Sample

	Rating = 1 (N=3643)				Rating = 2 (N=3643)			
	Mean	Std Dev	min	max	Mean	Std Dev	min	max
lsize	13.34	1.81	9.44	17.06	13.36	1.80	7.60	17.06
lzscore1	1.49	1.49	-2.45	31.20	1.49	1.57	-2.45	31.20
lzscore2	0.62	1.18	-6.78	9.74	0.54	1.04	-6.78	10.37
lstate_own2	0.61	0.49	0	1	0.63	0.48	0	1
lfd	0.19	0.39	0	1	0.18	0.38	0	1
num_years_pre	1.32	0.64	-2.43	2.52	1.37	0.65	-2.43	2.52
num_loans_pre	2.36	0.97	0.00	5.04	2.55	0.97	0.00	5.04
ave_loan_pre	19.72	1.45	16.81	23.72	19.74	1.41	16.81	23.72
total_loan_pre	22.09	1.84	18.32	27.43	22.30	1.75	18.32	27.43
lT1	0.06	0.34	-1.73	3.00	0.06	0.30	-1.73	2.55
lT2	0.11	0.30	-1.92	1.81	0.11	0.23	-1.92	1.81
lT3	0.03	0.08	-0.40	0.56	0.02	0.08	-0.40	0.96
lT4	1.08	1.29	-0.48	26.89	1.02	1.36	-0.48	22.16
lT5	0.82	1.05	0.00	12.35	0.87	1.18	0.00	19.22
lT4_1	0.64	0.66	0.01	7.71	0.63	0.44	0.04	7.71

Table 3.9 Step 3 Test 3 Result: Probit Regressions for the Likelihood of Loan Default, and Financial Distress on Lag ratings

This table shows marginal effects of probit regressions predicting the likelihood of a firm having a loan default or financial distress. The dependent variable in column (1) is one if a firm has a loan default for that year and zero otherwise. It follows the model: $P(LD_t) = R2_{t-1} + a_{t-1} + b_i$. The dependent variable in column (2) is one if a firm experience financial distress for that year and zero otherwise. It follows the model: $P(FD_t) = R2_{t-1} + a_{t-1} + b_i$. a_{t-1} and b_i are time and industry fixed effects; and *R2*, *LD*, and *FD* are all dummy variables. *R2* stands for rating 2, and *R2* =1 when ICR = 2, and *R2* = 0 when ICR = 1. *LD* stands for loan default, and *LD* = 1 when ICR = (3, 4 or 5), and *LD* = 0 when ICR = (1 or 2). *FD* stands for financial distress and it is calculated as $FD_t = 0, when\ EBIT_{(End-of-Year)t}/Interest\ Payment_{(Entire\ Year)t} \geq 1$; and $FD_t = 1,\ Otherwise$. Tests are done with both year and industry fixed effects. The intercepts are not reported. Robustness standard errors are clustered at the customer level and reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	Matched Sample		Above-mean Matched Sample	
	(1)	(2)	(3)	(4)
	LD	FD	LD	FD
$R2_{t-1}$	0.6127***	0.2665***	0.3655***	0.226***
	(0.0809)	(0.0577)	(0.1055)	(0.0872)
# of 1s	484	848	359	485
# of 0s	3576	3212	1728	1602
N	4060	4060	2087	2087
N-cluster	1351	1351	814	814

Table 3.10 Descriptive Statistic of Beijing and Guangdoing Sample

Panel A: Beijing Sample

year	Annual Percentage of Financially Distressed Firms Among all Firms with Rollover Loans of That Year			Annual Percentage of Defaulted Loans Among all Rollover Loans of That Year		
	Number FD Firms	Number Rollover Firms	Distressed / Rollover Firms	Num Default Loans	Num Rollover Loans	Default / Rollover Loans
1998	0	2814	0%	2448	9934	25%
1999	2405	2614	92%	3152	8372	38%
2000	1987	2233	89%	2013	6454	31%
2001	1551	1679	92%	1448	4720	31%
2002	1234	1351	91%	1222	4110	30%
2003	960	1067	90%	996	3216	31%
2004	558	626	89%	296	1711	17%
2005	299	335	89%	353	874	40%
2006	87	118	74%	41	375	11%
2007	26	69	38%	0	322	0%
2008	34	68	50%	3	278	1%
2009	12	32	38%	0	127	0%

Panel B: Guangdong Sample

year	Annual Percentage of Financially Distressed Firms Among all Firms with Rollover Loans of That Year			Annual Percentage of Defaulted Loans Among all Rollover Loans of That Year		
	Number FD Firms	Number Rollover Firms	Distressed / Rollover Firms	Num Default Loans	Num Rollover Loans	Default / Rollover Loans
1998	0	6421	0%	6329	15183	42%
1999	3643	3819	95%	2669	8882	30%
2000	3152	3332	95%	730	8266	9%
2001	2419	2556	95%	667	6041	11%
2002	1963	2077	95%	581	4785	12%
2003	1504	1589	95%	389	3679	11%
2004	1201	1272	94%	6620	9068	73%
2005	435	464	94%	390	1275	31%
2006	353	412	86%	222	1301	17%
2007	259	377	69%	32	1174	3%
2008	234	289	81%	44	902	5%
2009	97	170	57%	31	520	6%

Table 3.11 Probit Regressions for the Likelihood of Getting Rollover Loans

Liquidity, profitability, productivity, leverage and turnover corresponds to T1, T2, T3, T4 and T5 as in Z-score 1. Tests are done with both year and industry fixed effects. The intercepts are not reported. Robustness standard errors are clustered at the customer level and reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	Beijing Sample	Guangdong Sample
post	-2.3632***	-1.1257***
	(0.1911)	(0.0949)
lSize1	-3.05E-10	-2.58E-09
	(3.38E-10)	(1.75E-09)
lFD1	0.3239***	0.5253***
	(0.0644)	(0.0288)
lLeverage1	-0.00633**	0.000441
	(0.0028)	(0.00063)
lLiquidity1	-0.1115	-0.0581
	(0.0897)	(0.069)
lProfit1	0.0447	0.000082
	(0.0347)	(0.000454)
lTurnOver1	-0.00014**	-0.00003
	(0.000072)	(0.000039)
lProductivity1	8.18E-07	-0.00001**
	(8.82E-07)	(4.78E-06)
post_lSize1	2.82E-10	2.69E-09
	(3.39E-10)	(1.75E-09)
post_lFD1	0.1264	-0.087
	(0.223)	(0.0731)
post_lLeverage1	0.2821	0.0462
	(0.2312)	(0.0379)
post_lLiquidity1	0.0368	-0.0421
	(0.1067)	(0.083)
post_lProfit1	-0.8403*	-1.3298***
	(0.4763)	(0.217)
post_lTurnOver1	0.000053	2.86E-06
	(0.000093)	(0.000049)
post_lProductivity1	-0.0002	-0.00141
	(0.000433)	(0.00262)
R-square	0.3178	0.1976
Max-rescaled R-square	0.4857	0.273
N-cluster	4453	21264
rollover loans	10259	17968
non-rollover loans	2951	34427

Table 3.12 Probit Regressions for the Likelihood of Getting Rating 2 VS. 1

- 2 ratings regression for all industries

This table provides results on 2 ratings (2 vs. 1) regressions on lag values of firms' hard information. Liquidity, profitability, productivity, leverage and turnover corresponds to T1, T2, T3, T4 and T5 as in Z-score 1. Tests are done with both year and industry fixed effects. The intercepts are not reported. Robustness standard errors are clustered at the customer level. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Beijing Sample

	Pre-2005 sample w/o replacement	Pre-2005 sample with replacement	Post-2005
Size1	-0.073***	-0.0726***	-0.0255***
	(0.0067)	(0.0074)	(0.0056)
lFD1	0.0014	0.0029	0.0033**
	(0.0016)	(0.0022)	(0.0015)
lLeverage1	0.3387***	0.3388***	0.303***
	(0.0632)	(0.0705)	(0.0939)
lLiquidity1	-0.1677***	-0.2023***	-0.0947
	(0.0458)	(0.057)	(0.0598)
lProfit1	-0.6555***	-0.6726***	-0.7425***
	(0.1457)	(0.16)	(0.2046)
lTurnOver1	-0.0003	-0.0012	0.0003
	(0.0006)	(0.0008)	(0.0006)
lProductivity1	0.0017***	0.0016***	0.0005
	(0.0004)	(0.0006)	(0.0005)
R-square	0.1465	0.1493	0.0892
Max-rescaled R-square	0.1955	0.1991	0.1317
N	5017	3913	5438
N-cluster	2519	2252	1968
rating=1 (bad ratings)	2587	1982	1377
rating=0(good ratings)	2430	1931	4061

Panel B. Guangdong Sample

	Pre-2005 sample w/o replacement	Pre-2005 sample with replacement	Post-2005
lSize1	-0.0673***	-0.0646***	-0.0237***
	(0.0029)	(0.0033)	(0.0039)
lFD1	0.0015***	0.0017***	0.0032***
	(0.0005)	(0.0006)	(0.0006)
lLeverage1	0.0979***	0.1171***	0.3467***
	(0.0205)	(0.0242)	(0.0486)
lLiquidity1	-0.0221	-0.0143	-0.0224
	(0.0171)	(0.0192)	(0.0185)
lProfit1	-0.6016***	-0.596***	-0.6661***
	(0.053)	(0.0606)	(0.0812)
lTurnOver1	0.000003	0.00009	0.0008***
	(0.0002)	(0.0002)	(0.0002)
lProductivity1	0.0041***	0.0035***	0.0065***
	(0.0007)	(0.0009)	(0.0008)
R-square	0.0729	0.0709	0.0553
Max-rescaled R-square	0.0973	0.0946	0.0969
N	32004	22579	37123
N-cluster	12478	11129	12576
rating=1 (bad ratings)	15048	10799	5566
rating=0(good ratings)	16956	11780	31557

Table 3.13 Robustness check: probit regressions for the Likelihood of Getting Rating 2 VS. 1

- 2 ratings regression on manufacturing industry only

This table provide results on 2 ratings (2 vs. 1) regressions on lag values of firms' hard information. Liquidity, profitability, productivity, leverage and turnover corresponds to T1, T2, T3, T4 and T5 as in Z-score 1. Tests are done with both year and industry fixed effects. The intercepts are not reported. Robustness standard errors are clustered at the customer level. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Beijing Sample

	Pre-2005 sample w/o replacement	Pre-2005 sample with replacement	Post-2005
lSize	-0.3934***	-0.3512***	-0.6555**
	(0.1156)	(0.0918)	(0.2603)
lFD	-0.0131	0.1144	-0.2262
	(0.0825)	(0.0915)	(0.1455)
lLeverage	0.1342***	0.1723***	0.1544***
	(0.0386)	(0.0441)	(0.056)
lLiquidity	-0.2264***	-0.2683***	-0.1097
	(0.0562)	(0.0602)	(0.0905)
lProfit	-0.2927***	-0.2031***	-0.1205*
	(0.0566)	(0.0584)	(0.0706)
lTurnOver	-0.1276**	-0.0769	-0.1249
	(0.062)	(0.0671)	(0.0767)
lProductivity	0.3684***	0.05	0.1123
	(0.1158)	(0.1243)	(0.1844)
R-square	0.1701	0.1555	0.1484
Max-rescaled R-square	0.2268	0.2074	0.2101
N	1750	1447	1764
N-cluster	971	878	658
rating=1 (bad ratings)	865	718	532
rating=0(good ratings)	885	729	1232

Panel B. Guangdong Sample

	Pre-2005 sample w/o replacement	Pre-2005 sample with replacement	Post-2005
lSize	-0.2834***	-0.3168***	-0.0744***
	(0.0204)	(0.0247)	(0.0237)
lFD	0.3591***	0.353***	0.2767***
	(0.0261)	(0.0297)	(0.0247)
lLeverage	0.2053***	0.2117***	0.1906***
	(0.0174)	(0.0211)	(0.0254)
lLiquidity	0.0134	0.0431**	-0.0064
	(0.0169)	(0.0197)	(0.0225)
lProfit	-0.2684***	-0.2527***	-0.1792***
	(0.0179)	(0.021)	(0.0243)
lTurnOver	-0.0302	-0.0356	-0.082***
	(0.0237)	(0.0268)	(0.0303)
lProductivity	0.2383***	0.2594***	0.1865***
	(0.0346)	(0.0413)	(0.0409)
R-square	0.0994	0.0995	0.0629
Max-rescaled R-square	0.1329	0.1329	0.1126
N	15716	10898	18124
N-cluster	5882	5218	6086
rating=1 (bad ratings)	7154	5029	2578
rating=0(good ratings)	8562	5869	15546

Table 3.14 Probit Regressions for the Likelihood of Loan Default, and Financial Distress on Lag ratings

(for all industries and for Beijing Sample only)

This table shows marginal effects of probit regressions predicting the likelihood of a firm having a loan default or financial distress. The dependent variable in columns (1) is one if a firm has a loan default for that year and zero otherwise. It follows the model: $P(LD_t) = R2_{t-1} + a_{t-1} + b_i$. The dependent variable in column (2) is one if a firm experience financial distress for that year and zero otherwise. It follows the model: $P(FD_t) = R2_{t-1} + a_{t-1} + b_i$. a_{t-1} and b_i are time and industry fixed effects; and *R2*, *LD*, and *FD* are all dummy variables. *R2* stands for rating 2, and *R2* =1 when ICR = 2, and *R2* = 0 when ICR = 1. *LD* stands for loan default, and *LD* = 1 when ICR = (3, 4 or 5), and *LD* = 0 when ICR = (1 or 2). *FD* stands for financial distress and it is calculated as $FD_t = 0, when\ EBIT_{(End-of-Year)t}/Interest\ Payment_{(Entire\ Year)t} \geq 1$; and $FD_t = 1,\ Otherwise$. Tests are done with both year and industry fixed effects. The intercepts are not reported. Robustness standard errors are clustered at the customer level and reported in parenthesis. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	LD					FD				
	Pre-period	Post-period	entire period	entire period	entire period	Pre-period	Post-period	entire period	entire period	entire period
$R2_{t-1}$	0.7589***	3.4999***		0.7802***	0.7496***	0.4473***	0.6098***		0.5041***	0.4386***
	(0.0714)	(0.2075)		(0.0636)	(0.064)	(0.0567)	(0.2037)		(0.0544)	(0.056)
$post$			-4.0836***		-3.4656***			-1.2873***		-0.9939***
			(0.0304)		(0.0629)			(0.1414)		(0.1445)
$R2_{t-1} * post$			3.7296***	-0.4855***	2.9782***			0.4117**	-1.0066***	-0.0187
			(0.16)	(0.1604)	(0.1721)			(0.1875)	(0.1321)	(0.1947)
# of 1s	746	10	756	756	756	4951	115	5066	5066	5066
# of 0s	5252	310	5562	5562	5562	864	112	976	976	976
N	5998	320	6318	6318	6318	5815	227	6042	6042	6042
N-cluster	2057	213	2123	2123	2123	2009	181	2052	2052	2052

Table 3.15 Definitions of Variables

Variable names	Baseline model variable	Alternative model variables
Size	Size = log(total assets)	1. Log (net operating income); 2. Log(total assets – fees to be apportioned – prepaid assets – notes receivable – net receivables - long-term investment - invisible assets – deferral taxes and credit) 3. Log(total ownership interest + few partner rights – invisible assets – fees to be apportioned – prepaid assets – deferral taxes and credit)

Z-score	Zscore1	Zscore2
		lzscore1_ave=mean(zscore1t-1,zscore1t-2);
		lzscore2_ave=mean(zscore2t-1,zscore2t-2);
		lT1_ave = average (lagT1,lag2T1);
		lT2_ave = average (lagT2,lag2T2);
		lT3_ave = average (lagT3,lag2T3);
		lT4_ave = average (lagT4,lag2T4);
		lT5_ave = average (lagT5,lag2T5);
		lT4_1_ave = average (lagT4_1,lag2T4_1)

fd	*FDt* = 0 when EBIT at End of year t / Interest Payment Entire Year t >=1; *FDt* = 1 Otherwise	
Ld_io	Ld_io = 1 if ld=1 or io=1; Ld_io=0 otherwise; ld = 1 if ICR = (3,4,5), ld=0 otherwise; io = 1 if interest over due flag = 1;io=0 otherwise	
State_own	State_own = 1 if state ownership indicator is 1; State_own = 0 otherwise	
emphasis	Emphasis = 1 if emphasis flag from the database = 1; emphasis = 0 otherwise	

Continued on the next page

Table 3.15 Definitions of Variables (Continued)

Variable names	Baseline model variable	Alternative model variables
Relationship measures	Num_years_pre = log(bank firm years)	Num_loans_pre = log(number of loans) Ave_loans_pre = log (average loan amount) total_loans_pre = log(total loan amount) Num_years_dummy = 1 if bank firm years of this firm >= mean (bank firm years of all sample firms); = 0 otherwise; Num_loans_dummy = 1 if number of loans of this firm >= mean (number of loans of all sample firms); = 0 otherwise; Ave_loans_dummy = 1 if average loan amount issued by the Bank to this firm >= mean (average loan amount issued by the Bank to all sample firms); = 0 otherwise; total_loans_dummy = 1 if total loan amount issued by the Bank to this firm >= mean (total loan amount issued by the Bank to all sample firms); = 0 otherwise

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