ESSAYS ON BANK LOAN CONTRACTS

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ABSTRACT

Jensen and Meckling (1976) depict the firm as a nexus of financial contracts that offer optimal mechanisms to mitigate various frictions between agents, e.g., equity holders versus debt holders, principal versus agent, etc. In this study, we focus on two particular types of loan contract, performance pricing and revolving line of credit.

Chapter 1 examines how default risk and accounting quality of borrowers affect the likelihood of using performance pricing in bank loan contracts. Consistent with the notion of negative hedging, higher default risk firms are less likely to use performance pricing loans. We also find that firms with poorer accounting quality are less likely to receive performance pricing loans. Stronger lender-borrower relationship that would mitigate information asymmetry and enhance monitoring, is found to be associated with greater likelihood of using performance pricing loans. In addition, we find that conditional on using performance pricing loans, firms with lower (higher) accounting quality are more likely to receive credit rating (accounting) based performance pricing provision. Furthermore, we document that the likelihood of receiving performance pricing loans is significantly reduced after borrowers’ accounting quality deteriorates, e.g., after they restate their financial reports. These results supports the positive accounting theory, suggesting that a significant cost associated with performance pricing loans is borrowers’ incentives to manipulate accounting information so as to obtain a lower loan spread.

Theoretical literature suggests that firms use lines of credit as a liquidity insurance to secure a desirable investment level in the event of future downturn (Tirole, 2005). In Chapter 2, we examine whether lines of credit provide liquidity insurance or simply

convenience to firms via focusing on the drawdown rate. We find that drawdown rate is on average significantly lower than the imputed market rate on a bank loan given the financial condition of a firm at the time of drawdown, which supports the theoretical notion that lines of credit offer liquidity insurance. In addition, we document that stronger (or existence of) prior lending relation is associated with a lower drawdown rate, however bank reputation has no impact on the drawdown rate. Furthermore, we find that the impact of lending relation on the drawdown rate only exists in borrowers subject to greater information asymmetry. While we document that borrowers are penalized (paying a higher spread and more likely pledging collateral) on new lines of credit issued after their drawdown, they are penalized much less as they borrow from high reputation banks. Our results suggest that bank reputation and lending relation help provide a more efficient liquidity insurance, however via different channels.

Chapter 3 examines how a firm's performance pricing loans affect manager's incentive to manipulate earning. We find that firms with a greater slope or convexity in their performance pricing loans have significantly larger discretionary accruals. However, the positive association between the slope or convexity of PSD and discretionary accruals is significantly reduced as the lenders are of higher reputation or have had a prior lending relationship with the borrowers. These results suggest that bank reputation and prior lending relation serve as an effective monitoring mechanism, which in turn mitigates managers' incentive to manage earnings.

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CHAPTER 1

ACCOUNTING QUALITY, DEFAULT RISK, AND PERFORMANCE PRICING LOANS

1. Introduction

Jensen and Meckling (1976) depict the firm as a nexus of financial contracts that offer optimal mechanisms to mitigate various frictions between agents, e.g., equity holders versus debt holders, principal versus agent, etc. In this study, we focus on a particular type of contract, performance pricing in bank loan contracts.

In contrast to traditional bank loans that are priced based on a fixed spread over LIBOR or prime rate, interest rate on performance pricing loans are based on LIBOR or prime rate plus a spread tied to borrowers' performance, e.g., credit rating or financial ratios like debt-to-EBITDA ratio. A typical performance pricing loan charges lower (higher) interest rates as borrower's performance becomes better (poorer). Performance pricing provision was not widely used in bank loan contracts until 1990s, when the loan market became larger and syndicate loans became an important source of corporate finance. In 1991, less than 1% of the loans in Dealscan had performance pricing provision. In contrast, performance pricing loans accounts for about 49% ($152 billion) of total bank loans issued in 2006.[1] Despite the wide use of performance pricing provision, there is limited research on its role in corporate lending. This paper intends to shed light on the determinants of using performance pricing provision in bank loan contracts.

Recent research has illuminated some possible benefits of using performance

[1] These numbers are based on our sample of 16,784 loans covering 3,604 firms from the Dealscan database.

pricing debts in the presence of various market frictions. First, Betty, Dichev and Weber (2002) and Asquith, Beatty and Weber (2005) argue that performance pricing loans align risk and reward of firm's performance/credit change in debt contract, and thereafter reduce recontracting cost. Second, Tchistyi (2006) develops a theoretical model in which performance pricing debts' higher interest rates associated with poor performance create a threat of losing control and thereby prevent the manager from extracting cash flow for personal use, which in turn reduces moral hazard problem between manager and equity holders. Thirdly, Manso, Strulovici and Tchistyi (2009) show that performance pricing provision can serve as a signaling or screening device in a setting with asymmetry information. In equilibrium, a manager who is expecting his firm to improve performance in the future would prefer performance pricing debts, while a pessimistic manager would prefer non-performance pricing debts. In summary, the performance pricing provision provides a mechanism in reducing renegotiation costs, moral hazard, and adverse selection in corporate lending.

While prior literature has been focusing on the benefits of performance pricing loans, there is little study on the cost of using this provision. If there are only benefits and no costs, all bank loan contracts should include performance pricing provision, however this is not the case. Based on our study of a sample of 16,784 loans during 1990-2007, about 37.5% of them are performance priced. Therefore, there must be some costs associated with using performance pricing in bank loan contracts.

In this paper, we attempt to identify the costs associated with performance pricing, and investigate how these costs affect the choice of using performance pricing loans. We propose two types of costs. The first one is that performance pricing might aggravate the costs of financial distress. Manso, Strulovici and Tchistyi (2009) illustrate in a model that in the presence of bankruptcy costs and tax benefits, performance pricing debts lead to earlier default, thereby a higher present value of bankruptcy costs and a lower ex ante firm value. This is because performance pricing debts impose a higher debt burden when the firm experiences financial constraint, which is like a negative hedging of future cash flows. The second cost is that performance pricing might increase the extent of borrowers' manipulation in accounting variables to achieve more favorable rates. This argument is in similar spirit as the "debt covenant" hypothesis in which managers make accounting choices to reduce the probability of violating accounting-based debt covenants (Dichev and Skinner, 2002; DeFond and Jiambalvo, 1994; Sweeney, 1994). Performance pricing offers managers an incentive to manipulate accounting information so as to pay a lower interest rate.

In this study, we examine whether and how the default risk and accounting quality affect the use of performance pricing provision in bank loan contracts. We document the following empirical findings. First, we document that firms with high default risk are less likely to use performance pricing in bank loans. Secondly, we find that firms with lower accounting quality are less likely to use performance pricing provision in their loan contracts. Thirdly, we find that prior lending relationship that proxies for information opacity between borrowers and lenders (delegated monitors) plays an important role in the use of performance pricing provision. After controlling for endogeneous choice of a lender, firms borrowed from a bank with a stronger prior lending relationship are more likely to receive performance pricing loans. Finally, we examine the change in the use of performance pricing loans around financial restatement events in which there is a significant change in perceived accounting quality. We find that the likelihood of using performance pricing loans is significantly reduced after financial restatement events.

Our paper contributes to the existing literature as follows. First, to the best of our knowledge, it is the first empirical study on potential costs of using performance pricing provision and how these costs affect the choice of using performance pricing loans. Secondly, this paper contributes to the literature in debt contracting by establish a link between accounting quality and the use of performance pricing provision. Thirdly, prior research on performance pricing loans has only focused on how borrower characteristics affect the use of performance pricing provision. We are the first to shed light on how lender characteristics and borrower-lender relationship would mitigate adverse selection and therefore affect the use of performance pricing provision.

The rest of this paper proceeds as follows. Section 2 provides a literature review and describes our hypotheses. Section 3 describes the data and summary statistics of our sample. Section 4 presents empirical results and section 5 concludes the paper.

2. Literature Review and Hypotheses Development

2.1. Benefits of Using Performance Pricing Debts

Prior research has demonstrated some possible benefits of using performance pricing debts to overcome various market frictions. First, Asquith, Beatty, and Weber (2005) suggest that performance pricing provisions help reduce re-contracting costs, since any improvement in the borrower's performance automatically decreases the interest rate on the loan. In the absence of performance pricing, such improvements would translate into lower interest rates only if the firm renegotiates with the lender or refinances. Similarly, marginal deterioration in performance would automatically lead to higher interest rates, whereas, in the absence of performance pricing, such increases are possible only if the firm actually violates a loan covenant and renegotiates with the lender.[2]

A second benefit to performance pricing is pointed out in theoretical work by Tchistyi (2006), who suggests that this could mitigate moral hazard problems. He argues that performance pricing leads to a higher interest rate when cash flows are lower, which in turn increases the likelihood of default. The resulting threat of losing control over the project induces the manager not to extract cash flow from the firm for personal use. In addition, Tchistyi (2006) shows that a scheme that punishes bad performance with higher interest rates could provide additional incentives for the manager to exert effort. Asquith, Beatty and Weber (2005) provide empirical evidence that firms with a higher probability of moral hazard are more likely to include interest-increasing performance pricing in their bank loan contracts.

Third, performance pricing could be used as a signaling and screening device in the presence of asymmetric information. Manso, Strulovici and Tchistyi (2009) develop a dynamic model where the future prospects of the firm are unknown to the market, but known to the manager (or equity holders). A manager who is optimistic about firm's future prospects (high-growth firm) would issue a performance pricing debt to signal its type, while a manager who is pessimistic about firm's future prospect (low-growth firm) would issue equity or fixed-interest debt. The low-growth firm does not want to mimic

[2] Roberts and Sufi (2008), however, find little evidence that the presence of performance pricing provision reduces the likelihood of renegotiation. Rather, they find that performance pricing provision appears to be used for the purpose of renegotiation design. For example, contracts with performance pricing provision are more likely to be unfavorably renegotiated for a negative deviation in accounting performance.

the high-growth firm because for a given performance pricing debt, the low-growth firm would likely pay higher interest in the future than the high-growth firm if it's true type is revealed. Consistent with this idea, Manso et al. (2009) find that firms choosing performance pricing loans are more likely to improve their credit ratings than firms choosing fixed-interest loans.

2.2. Costs of Using Performance Pricing Debts

While the few studies mentioned above discuss the benefits of adopting performance pricing provisions, there is little research on costs of adopting such provisions. Below, we discuss some potential costs of performance pricing and the resulting implications for the characteristics of borrowers and lenders that are likely to include such provisions in their contracts.

2.2.1. Accounting Manipulation and Performance Pricing

Performance pricing could increase the cost to the borrower through its effect on monitoring costs. If the lender incurs a higher monitoring cost for performance pricing loans, this gets passed on to the borrower. Of course, all loans have monitoring costs associated with them, but in the case of loans with performance pricing provisions, we argue that such costs are higher, because performance pricing creates incentives for borrowers to manipulate accounting information to achieve more favorable interest rates. Our argument here is based on positive accounting theory (Watts and Zimmerman, 1990), which suggests that managers have the incentive to make financial reporting decisions that reduce the likelihood of violating accounting-based covenants in debt contracts.

Several studies suggest that managers do respond to such incentives. DeFond and Jiambalvo (1994) document that managers use abnormal accruals to avoid debt covenant violation. Sweeney (1994) finds that managers make income-increasing accounting changes during periods prior to technical default. Dichev and Skinner (2002) document an unusually small number of loan/quarters with financial measures just below covenant thresholds and an unusually large number of loan/quarters with financial measures at or just above covenant thresholds. In contrast to loan covenants, where firms have incentives to manipulate earnings only when they are close to the covenant violation threshold, firms with performance pricing loans have greater incentives to manipulate accounting information, because even relatively small changes in earnings could translate into lower interest payments. Consistent with this, Beatty and Weber (2003) document that the performance pricing provision gives managers additional incentives to make income-increasing changes in accounting.

Of course, banks are aware of borrowers' incentive to manipulate accounting information, and monitor borrowers by collecting information and verifying the truthfulness of the accounting variables. Typically, a syndicated loan involves two types of lenders, lead arrangers and participant lenders. Lead arrangers establish and maintain a relationship with the borrower, and take on the primary responsibility of information collection and monitoring. In contrast, participant lenders rarely directly negotiate with the borrowing firm. Lead arrangers are compensated with a fee for arranging and managing the syndicated loan, in addition to interest and commitment fee income. Lead arrangers are 'informed lenders' and would monitor borrowers due to their large holding in bank loans, as well as their long-run reputation consideration. Nevertheless monitoring is costly, requiring lenders to spend time and resources in the acquisition and assessment of borrowers' information. Therefore the choice of using performance pricing loans will depend on the tradeoff between the benefits (e.g., mitigating moral hazard and adverse selection) and the costs of monitoring.

We identify two factors that affect the monitoring costs of banks. First, we expect that the cost of monitoring decreases in the quality of the borrower's accounting information (Costello and Wittenberg-Moerman, 2009). This leads us to the first hypothesis:

H1.1: All else equal, performance pricing provisions are less likely to be included in a loan contract if a borrower has lower accounting quality.

Many studies suggest that the perceived quality of a firm's financial statement is significantly negatively affected following financial restatements (Palmrose, Richardson, and Scholz 2004; Graham, Li and Qiu, 2008). Thus, we expect that the probability that a firm receives performance pricing loans following financial restatements is significantly lower. Or:

H1.1a: All else equal, performance pricing provisions are less likely to be included in a loan contract if the borrower has had a financial restatement event.

Second, the cost of bank monitoring should be lower if the bank has a prior lending relationship with the borrower. Through a long and continuing lending relationship, a bank could gather detailed information regarding the borrower's business operation and investment opportunities, and efficiently apply this knowledge in making decision of future lending business. Haubrich (1989) argues that in a repeated relationship between a bank and a borrower, the bank can keep track of reports from the borrower and penalize the borrower if too many reports are bad. Sufi (2007) finds that if there is limited information about a borrower, lead banks attempt to reduce the need for information gathering by choosing participants that are more likely to "know" the borrower through previous lending relationships. Furthermore, according to Diamond (1991), after servicing bank loans for a long time, a borrower establishes a solid credit reputation. Therefore, a prior lending relationship reduces information asymmetry, and thereby reduces monitoring costs. As a result, performance pricing is more likely to be included in a loan contract when there is a stronger prior lending relationship between the borrower and the bank. Thus, we have:

H1.2: All else equal, performance pricing is more likely to be included in a loan contract when the borrower has a stronger prior lending relationship with the lead bank.

2.2.2. Cost of Bankruptcy

Manso et al. (2009) demonstrate that performance pricing lead to earlier default, and therefore results in higher expected bankruptcy costs and a lower ex ante firm value. This is because performance pricing debts impose a higher debt burden when the firm experiences financial constraints, which is like a negative hedging of future cash flows. This cost of using performance pricing debt will be particularly greater if a firm is closer to financial distress or default, since any extra debt burden associated with deterioration of performance would precipitate default or costly renegotiation of debt contracts. As a result, we derive the following hypothesis:

H1.3: All else equal, firms with higher default risk are less likely to use performance pricing loans than firms with lower default risk.

3. Data and Summary Statistics

3.1. Data Source

Our sample of bank loans is obtained from the Dealscan database offered by Loan Pricing Corporation (LPC). Dealscan contains detailed information on bank loans worldwide, such as borrower and lender identity, loan amount, loan spread, issuing and maturity date, financial and general covenants etc. About 60% of loan data in Dealscan are collected from SEC filings, and the rest are obtained from direct contact with borrowers and lenders. According to Carey and Hrycay (1999), the Dealscan database covers between 50% and 75% commercial loans in the U.S. by 1992, and by 1995 it covers a greater fraction of commercial loans.

LPC reports loan data at the 'deal' level as well as 'facility level'. The basic unit of observation in Dealscan is a 'facility' or 'tranche'. Several facilities are often grouped into a deal. The facilities within a deal may differ in loan amounts, maturities, and other terms. In this study, we conduct our analyses at the facility level, since multiple facilities in a deal may have different choices of using performance pricing provision.

Our sample starts with all loans of U.S. borrowers from 1990 to 2007 recorded in the Dealscan database. We start our sample in 1990 because the data before 1990 are not comprehensive and do not cover a majority of commercial loans. Accounting data of borrowers are obtained from the Compustat database and stock return data are from the CRSP database. We hand match the firms in Dealscan with firms in the Compustat and CRSP based on their names. We exclude those borrowers that cannot be linked to Compustat and CRSP names, as well as observations with missing values in relevant firm characteristic variables. This procedure results in our main sample of 16,784 facilities borrowed by 3,604 companies.

We obtain financial restatement data during January 1, 1997 and June 30, 2006 from the Financial Restatement Database of U.S. General Accounting Office (GAO). GAO collects data from public source, Lexis-Nexis on-line information service and SEC filing. This database includes a list of "financial restatements identified as having been made because of accounting irregularities." The irregularities represent "so-called 'aggressive' accounting practices, intentional and unintentional misuse of facts applied to financial statements, oversight or misinterpretation of accounting rules, and fraud."[3] Thus, it is appropriate to assume that the restatements included in the database are caused by intentional misapplication of GAAP.

3.2. Firm Characteristic Variables

To examine our hypotheses above on the effect of accounting quality, default risk, and bank-borrower prior lending relationship on the likelihood of using performance pricing in loan contract, we construct the following variables. Detailed variable definitions are provided in Appendix A.

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[3] From GAO letter to Senator Sarbanes in 2002 and GAO letter to Senator Sarbanes on 1/17/2003.

3.2.1. Accounting Quality

To measure accounting quality, we construct an accrual quality measure following Dechow and Dichev (2002). The standard deviation of residuals of the following equation over the years *t*-9 through *t:*

$$CA_{j,t}=c+\varphi_1 CFO_{j,t-1}+ \varphi_2 CFO_{j,t}+\varphi_3 CFO_{j,t+1}+ \upsilon_{j,t}, \qquad (1.1)$$

where $CA_{j,t}$ = *total current accruals* = *Δcurrent assets(Compustat item 4) - Δcurrent liabilities(item 5)- Δcash(item 1)+ Δdebt in current liabilities(item 34), Δ = change from year t to year t-1, CFO = cash flow from operation = net income before extraordinary item (item 18) - total accruals, and total accruals = current accruals-depreciation and amortization expense (item 14).* All variables are scaled by assets of that year. Estimation of Dechow and Dichev (2002, hereafter DD) model involves two steps. First, we estimate above equation annually for each firm for each of the ten years *t*-9 through *t*. Then we calculate the standard deviation of firm *j*'s residuals across the ten years, i.e., $\upsilon_{j,t}$ through $\upsilon_{j,t-9}$, and obtain an accrual quality measure of DD_AQ10. We also compute accrual quality by estimating equation (1.1) over the years *t*-4 through *t,* and obtain an alternatively measure of DD_AQ5. A large value of DD_AQ10 or DD_AQ5 indicates poor accounting quality, and we expect it to have a negative effect on the use of performance pricing provision according to hypothesis *H1.1*.

In additional, we construct alternative measures of accounting quality. Following McNichols (2002), we control for changes in sales revenue and property, plant and equipment (PPE) in equation (1.2):

$$CA_{j,t}=c+\varphi_1 CFO_{j,t-1}+ \varphi_2 CFO_{j,t}+\varphi_3 CFO_{j,t+1}++ \varphi_4 \Delta Sales_{j,t}++ \varphi_5 PPE_{j,t} +\upsilon_{j,t}, \qquad (1.2)$$

where *sales = total revenues (item 12) and PPE = property, plant, and equipment (item*

7). All variables are scaled by assets of that year. Accrual quality measure MDD_AQ10 is the standard deviation of firm *j*'s residuals across the ten years, i.e., $\upsilon_{j,t}$ through $\upsilon_{j,t-9}$, and MDD_AQ5 is the standard deviation of firm *j*'s residuals by estimating equation (1.2) over the years *t*-4 through *t.*

As a robustness check, we also compute the average absolute value of the residuals from equation (1.1) or (1.2) over the years *t*-9 through *t or* the years *t*-4 through *t*, and obtain four more accrual quality measures ADD_AQ10, ADD_AQ5, AMDD_AQ10, AMDD_AQ5. Detailed definitions of these variables are explained in Appendix A.

3.2.2. Measures of Default Risk

We adopt several proxies for firm's default risk, including Altman's Z-score (*Zscore*), Ohlson's O-score (*Oscore*), credit rating, stock return volatility (*Retstd*), and cash flow volatility (*CFstd*). *Zscore* and *Oscore* are computed based on Altman (1968) and Ohlson (1980). *Credit rating* is constructed by converting the Standard & Poor's Senior Credit Rating into numeric values. Credit rating of AAA is assigned with a value of 22, AA^{+} with 21, …, D with 1, and a value of 0 is assigned if the rating is not available. *Retstd* is calculated as the standard deviation of twelve monthly returns during the previous calendar year. *CFstd* is defined as the standard deviation of net cash flows over the past sixteen quarters (four years) divided by the average quarterly book value of assets over the same period. To assess the overall impact of default risk, we construct a default risk index. We rank each of the five variables (*Zscore, Oscore, credit rating, Retstd,* and *CFstd)* into deciles, with the highest default risk firm taking a value of 10 and the lowest one taking a value of 1. Five ranks are summed and then divided by 50. Thus the default index ranges from 0.1 to 1, with larger values representing higher default firms. We expect it to have a negative effect on the use of performance pricing provision according to hypothesis *H1.3.*

3.2.3. Other Firm Characteristic Control Variables

In addition to the variables discussed above, we also control for other firm characteristics (firm size, market-to-book ratio, and ROA) that might affect the choice of using performance pricing loans and other debt contract terms. We measure firm size using the natural logarithm of total assets. Larger firms are in general more transparent because of more analyst coverage. On the other hand, the benefits of manipulating accounting information would be greater for larger firms. Kim, Liu and Rhee (2003) find that both large and small firms manage earnings aggressively. While small firms are more likely to manage earnings to avoid reporting losses, large- and medium-sized firms exhibit more aggressive earning management to avoid reporting earning decreases. Therefore, the effect of firm size on the use of performance pricing loans is not clear. *Market-to-book ratio* is used to proxy for firm's growth opportunities. It is defined as the ratio of market value of assets (book value of debt plus market value of equity) and book value of total assets. According to Manso, Strulovici and Tchistyi (2009), performance pricing could be used to signal firm's future growth potential, therefore we expect a positive relationship between *Market-to-book ratio* and the use of performance pricing. We also control for firm performance that is proxied by *ROA* (operating income divided by total assets).

3.3. Loan Characteristic Variables

Since contract terms of a bank loan are likely to be jointly determined, we are interested in studying how other loan characteristics would affect the use of the performance pricing provision. Thus we include many loan-specific variables in explaining the choice of using performance pricing, including loan size, loan maturity, loan type, secured or not, seniority, whether a loan has any covenant, and whether a loan is syndicated. The larger is the loan size and the longer is the maturity, the greater are the expected renegotiation costs. Therefore, we expect loan size and maturity to have a positive effect on the use of the performance pricing provision.

Bank loans in the Dealscan database could be categorized into two groups: term loan and revolving line of credit. With a term loan, a complete withdrawal of funds is required on deal inception and the full amount of loan is subject to repayment before maturity. With a revolving loan, borrowers may obtain additional funds if the line of credit is not fully drawn. Since lines of credit are used for corporate liquid management (Sufi, 2009), borrowers would have an incentive to obtain greater amount of funds in a revolver as their financial conditions deteriorate. Therefore, the performance pricing provision is more likely to be included in a revolver so as to mitigate ex post opportunistic behavior of borrowers. We define a dummy variable *Revolver* which is equal to one if the loan is a revolver and zero otherwise.

If a loan is secured, the expected loss of the lender is lower, thereby the cost of monitoring by the lender will be lower. Thus, whether the loan is secured will be positively related to the use of performance pricing provision. We define a dummy variable *Secured* that is equal to one if the loan is secured and zero otherwise. By the same token, a senior loan would be more likely performance priced. We define *Senior* as a dummy variable that is equal to one if the loan is senior and zero otherwise.

Beatty, Dichev and Weber (2002) find that the performance pricing provision and debt covenants tend to be bundled in the same loan contract. While the performance pricing provision is used to handle credit risk improvement, covenant provisions are used to handle extreme credit risk deterioration. Thus we expect a positive association between the performance pricing provision and the debt covenant usage. We include a *Covenant* dummy in our analysis, which is equal to one if either financial or general covenant is included in the contract, and zero otherwise.

Asquith, Beatty and Weber (2005) argue that whether a loan is syndicated serves as a proxy for expected renegotiation costs. This is because syndicated loans require the agreement of a majority or supermajority of lenders to enact changes in the contract, which is likely to be more costly. Therefore we expect syndicated loans are more likely to be performance priced. We define a *Syndicate* dummy that is equal to one if a loan is syndicated and zero otherwise.

3.4. Lead Bank-Borrower Prior Lending Relation

To assess how prior lending relationship affects the choice of using performance pricing, we construct a variable to capture the strength of prior lending relationship between a lead bank and a borrower. While most of loans in Dealscan involve several lenders, it is the lead arrangers' responsibility to negotiate directly with the borrower and monitor contractual terms.[4] Our analysis on lender characteristics will then focus on lead

[4] Participant lenders rarely directly negotiate with the borrowing firm and usually hold a relatively small share of the loan.

arrangers. Following Sufi (2007), we classify lenders listed in "Lender-Lead Arranger" as lead arranger if this variable is available from the custom report of Dealscan. Otherwise, we classify lenders having a "lead role" listed in "Lenders-All lenders" as the lead arranger. To make data collection manageable, we focus on the top 100 lead arrangers in Sufi (2007). This selection will not result in any bias, because according to Sufi (2007), the top 100 lenders represent about 96% of the total number of loans. To take into account bank mergers during our sample period, we track all mergers and acquisitions of financial institutions, and allow the acquiring banks to inherit all the lending history of the acquired bank after the acquisition date. For example, in April 1998, First Union Corp. acquired CoreStates Financial Corp. with a name of merged entity 'First Union Corp.' Thus after April 1998, First Union Corp. inherited CoreStates' entire lending history as we compute lender market share and lead bank-borrower relation.

Following previous literature (e.g., Bharath, Dahiya, Saunders, and Srinivasan, 2007), strength of lead bank-borrower prior lending relation ($) is computed as the dollar amount of loans arranged by a particular lead bank and its predecessors for a firm during the previous 5 years divided by the total dollar amount of loans borrowed by the firm during the same period. While this measure of relation captures the intensity of lending, we also construct an alternative measure that focuses on the existence of a prior lending relation. Strength of lead bank-borrower prior lending relation (N) is computed as the number of loans arranged by a particular lead bank and its predecessors for a firm during the previous 5 years divided by the total number of loans borrowed by the firm during the same period. According to Hypothesis *H1.2*, prior bank-borrower lending relation will have a positive effect on the likelihood of using performance pricing loans.

3.5. Summary Statistics

We present summary statistics of our sample in Table 1.1. As shown in Panel A, there are a total of 16,784 loan facilities from 1990 to 2007 in our sample. Of these, 6,294 (37.5%) are performance pricing loans and 10,490 (62.5%) are non-performance pricing loans.[5] By dollar value, performance pricing loans account for 46.45% ($1.61 trillion) of total bank loans (3.72 trillion). Figure 1.1 displays the percentage of performance pricing loans for each year from 1990 to 2007. The percentage of performance pricing loans increased dramatically during 1993-1995. Panel B of Table 1.1 reports the distribution of performance pricing loans based on the types of performance measures. There are more than eight performance measures in our sample. The most commonly used measure is debt-to-EBITDA ratio, which accounts for about half of the performance pricing loans. The second widely used performance measure is Senior Debt Rating, which accounts for about 22.3% of the performance pricing loans. All the other performance measures account for a small portion of the sample.

In Panel C, we compare various characteristics between performance pricing and non-performance pricing loans. The average size of the performance pricing loans is $256 million, which is statistically significantly larger than the average size of non-performance pricing loans, which is $177 million. Performance pricing loans are generally longer in maturity, more likely to be a revolver, more likely to be secured and senior debt, more likely to have a financial or general covenant, and more likely to be syndicated than non-performance pricing loans. The differences between the two groups

[5] Among the 6,294 performance pricing loans, 404 loans involve more than one performance measure. This leaves us with 5,890 performance pricing loans containing only one performance measure.

are all statistically significant at 1% level. Borrowers of performance pricing loans are associated with higher growth potential and less volatile stock returns, lower leverage ratio and lower default risk, higher profitability, and better credit quality. These results imply that firms with lower default risk and better performance are more likely to use performance pricing loans.

The lender-borrower relation variables indicate that lead banks issuing performance pricing loans tend to have a closer relationship with the borrowers. Panel C also shows that compared to those using non-performance pricing loans, borrowers of performance pricing loans are associated with lower *Accrual measure* (higher accounting quality). The difference is statistically significant.

In summary, our univariate results are consistent with our hypotheses above. Nevertheless, the choice of using performance pricing might be affected by many loan-specific, firm-specific, and lender-specific characteristics. Therefore it is important to examine our hypotheses in a multivariate framework.

4. Empirical Results

4.1. Accounting Quality and Performance Pricing

As we discussed above, performance pricing might provide an incentive for managers to manipulate accounting information so as to achieve a more favorable interest rate. Since lenders perceive this incentive, we expect that firms with lower accounting quality are less likely to obtain performance pricing loans. To examine this hypothesis, we estimate the following logit models:

$$P(performance\ pricing\ loan) = \alpha_1 + \beta_1 Accrual\ measure + \sum_i \gamma_i Control\ variables + \varepsilon_t, \quad (1.3)$$

In equations (1.3), we examine the effect of *Accrual measure* on the choice of using performance pricing loans, after controlling for other firm-specific and loan-specific characteristic variables. Hypothesis *H1.1* implies that the coefficient of β_1 should be negative since a high *Accrual measure* represents low accounting quality. In equation (1.3), the dependent variable is a dummy which is equal to one if the loan contract includes performance pricing provision and zero otherwise. The right-hand-side variables include a measure of *Accrual measure* and control variables that capture firm-specific and loan-specific characteristics described above. The regression results are reported in Table 1.2.

As shown in models (1)-(8), the coefficient estimates of all *Accrual measures* are negative and highly significant, suggesting that the performance pricing provision is less likely to be used when the borrower has a poorer accounting quality. In terms of economic magnitude, an increase of one STD in *Accrual measure* is associated with a decrease of 2.39% in the conditional probability of using performance pricing loans, based on model (1.3), holding all variables at their median values. The coefficient estimates of other control variables in Table 1.2 are generally consistent with the theoretical framework outlined above. Performance pricing provision is more likely to be used when firms are smaller, more profitable, when the loan is larger, longer in maturity, secured, syndicated, and when the loan is a revolver and has a general or financial covenant. The coefficients of *Syndicate* are positive and significant. For a syndicate loan, it is more costly to achieve agreement of a majority or supermajority of lenders to enact changes in the loan contract, which make performance pricing loans particularly appealing.

4.2. Default Risk and Performance Pricing

As we discussed above in hypothesis *H1.3*, performance pricing loans would lead to early default and increase expected bankruptcy costs. Thus firms with higher default risk would be less likely to use performance pricing loans. To examine the relationship between default risk and the choice of using performance pricing, we estimate the following logit model in equation (1.4):

$$P(\mathit{performance\ pricing\ loan}) = \alpha_3 + \beta_1 \mathit{Accrual\ measure} + \beta_3 \mathit{Default\ risk} + \sum_i \gamma_i \mathit{Control\ variables} + \varepsilon_t \quad (1.4)$$

In equation (1.4), the dependent variable is a dummy which is equal to one if the loan contract includes performance pricing provision and zero otherwise. The right-hand-side variables include a measure of default risk (*Credit rating*, *Retstd*, *CFstd*, *Zscore*, *Oscore*, or *default index*), *Accrual measure*, and other control variables. The regression results are reported in Table 1.3.

As shown in model (1), the coefficient estimate of *Credit rating* is positive and statistically significant, suggesting that higher rating firms (lower default risk) are more likely to use performance pricing loans. This result is consistent with hypothesis *H1.3*. We also find strong supportive evidence based on other proxies of default risk, except Altman's Z-score in model (4). The choice of using performance pricing loan is significantly negatively related to stock return volatility (*Retstd*), cash flow volatility (*CFstd*), and Ohlson's O-score (*Oscore*). However, the coefficient estimate of Altman's

Z-score *(Zscore*) is insignificant.

We have five proxy variables for default risk, and each might capture different aspects of default risk. In order to incorporate all these variables in one regression, we construct an index that ranks the relative default risk of each firm in our sample. The default index ranges from 0.1 to 1, with larger values representing higher default risk. As shown in model (6), the coefficient estimate of the *Default index* is negative and highly significant. In models (1)-(6), we also include *Accrual measure* (DD_AQ10), which is negative and significant. In model (7), we find that *Accrual measure* (MDD_AQ10) remains significantly negative after controlling for default index. These results suggest that accounting quality and default risk capture different costs associated with issuing performance pricing loans.

The effect of *Default index* on the choice of using performance pricing provision is also economically significant. Based on the magnitude of the coefficient estimate in model (6), an increase of one STD in *Default index* from its median is associated with a decrease of 4.72% in the likelihood of using performance pricing loans, holding all variables at their median values. Given that about 37.5% of our bank loan sample contains performance pricing provision, this is equivalent to a decrease of 12.59% in conditional probability. Overall these results lend strong support to our hypothesis *H1.3* that firms with greater default risk are less likely to use performance pricing provision in their loan contracts.

The coefficient estimates of other firm and loan characteristic variables are generally consistent with those reported in Table 1.2. Firms with lower default risk, smaller size, lower volatility, and greater profits are more likely to use performance pricing loans. The performance pricing provision is more likely to be included in loans that are larger in size, longer in maturity, revolver, secured, syndicated and containing financial or general covenants.

4.3. Performance Pricing and Financial Restatement

We have examined above the relationship between accounting quality and the use the performance pricing provision based on a large sample of bank loans. We find support to our hypothesis that firms with lower accounting quality are less likely to receive performance pricing loans. Nevertheless, we so far cannot say anything about the causality between accounting quality and the use of performance pricing provision. In this section, we rely on a sample of financial restatement events around which the perceived information environment and accounting quality change significantly, and then investigate the change in the use of performance pricing provision. This would provide us a much cleaner test on how accounting quality affect the use of performance pricing provision.

Several studies use financial restatement as a proxy for financial reporting quality, such as Myers et al. (2003), Palmrose and Scholz (2004). Restatement implies a loss of confidence in firm's accounting quality and creates greater information opacity (Kinney, Palmrose and Scholz, 2003). There are usually significant penalties following financial restatement of a company. Anderson and Yohn (2002) find negative returns for firms with revenue recognition issues and an increase in bid-ask spread for restated firms. Palmrose, Richardson and Scholz (2004) document an average abnormal return of about –9.2% over a 2-day window around restatement announcements. Hribar and Jenkins (2004) show that accounting restatements lead to increases in the firm's cost of equity capital and decreases in expected future earnings. Graham, Li and Qiu (2008) show that loan spread has significantly increased and other loan contract terms become more stringent after financial restatement. Prior studies all suggest that financial restatements imply lower accounting quality, which thereby leads to a higher cost of monitoring in issuing performance pricing loans. If accounting quality is a determinant of whether to include the performance pricing provision in bank loan contracts as we proposed above, we would expect a significant drop in the probability of receiving performance pricing loans after the financial restatement events.

To test this proposition, we will examine how the likelihood of using the performance pricing provision changes around restatement events. We start with a sample of financial restatement events during January 1, 1997 and June 30, 2006 from the Financial Restatement Database of U.S. General Accounting Office (GAO). Following Graham, Li and Qiu (2008), we only keep the first restatement if there is more than one restatement for a particular firm, which leaves us 1,183 restatements, representing 1,183 companies.[6] We focus on the restatement firms and estimate the following logit model (equation 1.5) to examine how the likelihood of using performance pricing provision changes after the restatement events.

$$P(performance\ pricing\ loan) = \alpha_4 + \beta_4 Post - restatement + \sum_i \gamma_i Control\ \mathrm{var}iables + \varepsilon_t, \quad (1.5)$$

[6] We keep the first restatement for each firm because we aim to examine the use of performance pricing provision before and after restatement events, and the post-restatement window of the first restatement is likely to overlap with the pre-restatement window of second restatement. This would be problematic in interpreting the results.

where *Post-restatement* is a dummy variable that equals one if a loan is issued after restatement events, and zero otherwise. We also include in the models those firm-specific and loan-specific variables as above. The variable of our interest is *Post-restatement*, which captures the change in the likelihood of using performance pricing loans before and after financial restatement events.

In models (1)-(2), we focus on bank loans issued during a six-year window (3 years before and 3 years after the restatement events), while in models (3)-(4), we focus on bank loans issued during a eight-year window (4 years before and 4 years after the restatement events). As shown in models (1) and (3), after we control for firm-specific and loan-specific characteristics, the coefficient estimate of *Post-restatement* is negative and significant at the 10% and 5% level respectively, suggesting that the likelihood of receiving performance price loans significantly decreases after a firm restates its financial statement. Based on the coefficient estimate of *Post-restatement* in model (1), we find that holding all other variables at their mean values, firms are 6.29% less likely to receive performance pricing loans after financial restatement compared to before the restatement events. This result lends support to our hypothesis H1a. In models (2) and (4), we include an additional variable, *Accrual measure* (DD_AQ10) and *Default index*. If the effect of financial restatement on the likelihood of using performance pricing provision is related to the deterioration of accounting quality or information environment, we expect that the coefficient estimate of *Post-restatement* would become smaller in magnitude or even insignificant after we control for accounting quality. This is indeed what we find. The coefficient estimate of the *Post-restatement* dummy remains negative but becomes insignificant or only marginal significant in model (2) and (4) respectively.

In summary, we document that the likelihood of using performance pricing loans is significantly reduced after financial restatement events, and the reduction in the use of performance pricing loans appears to be driven by the significant deterioration in accounting quality associated with the restatement events.

4.4. Prior Lending Relationship and Performance Pricing

As we argued above in developing hypothesis *H1.2*, banks with stronger prior lending relationship would be able to monitor more diligently and effectively, which in turn mitigates information asymmetry. As such these banks are more likely to offer performance pricing loans. To test hypothesis *H1*.2, we examine the effect of the prior lending relationship on the likelihood of issuing performance pricing loans.

It is noteworthy that the choice of bank and the extent of lending relationship is not exogenously given, instead it might be determined by certain characteristics of borrowers. For example, Dinc (2000) develops a theory and shows that higher reputation banks would offer loans with commitment to the highest quality borrowers, however an increase in credit market competition enhances banks' incentive to lend to borrowers in distress. Thus the effect of bank reputation and prior lending relation on the use of performance pricing loans might be driven by certain borrowers' characteristics.

To address the selection issue between borrowers and banks, we employ a two step instrumental variable approach. In the first stage, we regress the strength of bank-borrower prior lending relation ($) or (N) on a few borrower characteristics, including firm size, ROA, asset tangibility, and a dummy variable for accessing the public debt market, as shown in equation (1.6):[7]

$$\begin{aligned}&\left(\textit{Lead bank-borrower lending relation}\right)_t \\ &\quad = \lambda_0 + \lambda_1 \textit{Firm size}_{t\text{-}1} + \lambda_2 \textit{ROA}_{t\text{-}1} + \lambda_3 \textit{Asset Tangibility}_{t\text{-}1} \\ &\quad + \lambda_3 \textit{Rating dummy}_{t\text{-}1} + \varepsilon_t .\end{aligned} \tag{1.6}$$

The choice of these instruments is mainly based on Bharath et al. (2007). They show that borrowers' size, credit rating, assets tangibility are significantly related to a firm's use of a relationship bank for future loans. In the second stage, we estimate a logit model (as shown in equation (1.7)) in which the predicted value of *Lead bank-borrower lending relation* from the first step is used to explain the choice of using performance pricing loans, in addition to other variables we used above.

$$\begin{aligned}&P(\textit{performance pricing loan})_t \\ &\quad = \alpha_3 + \beta_2 \left(\textit{Predicted strength of prior lending relation}\right)_{\mathrm{t\text{-}1}} \\ &\quad + \sum_i \gamma_i \textit{Control variables}_{\mathrm{t\text{-}1}} + \varepsilon_{\mathrm{t}} .\end{aligned} \tag{1.7}$$

The regression results of the second stage are reported Table 1.5. As shown in models (1)-(2), even after controlling for default risk and accounting quality (DD_AQ10 or MDD_AQ10), the coefficient estimate on *predicted strength of prior lending relation* ($) is positive and significant at the 5% level. The results are similar as we include an alternative measure of relationship: *predicted strength of prior lending relation* (N) in models (3)-(4). In summary, lenders appear more likely to issue performance pricing loans to those firms with a stronger prior lending relationship.[8] These results are consistent with hypothesis *H1.2*, suggesting that stronger lender-borrower relationship would mitigate information asymmetry and enhance monitoring, which then lead to a

[7] We define that a firm has access to the public debt market if any type of S&P debt rating is available in the Compustat database.

[8] We obtain similar results if we replace *Lead bank-borrower lending relation* with *Lead bank-borrower lending relation (n)* in which prior lending relation is computed based on the number of loans instead of the amount of loans.

greater likelihood of using performance pricing loans.

4.5. The Choice of Using Accounting Based versus Rating Based Performance Pricing Loans

In above analysis, we study the impact of accounting quality and default risk on the choice between using performance pricing loans and non-performance pricing loans. In this section, we use probit models to examine how accounting quality affects the choices of using different types of performance measure. As shown in Panel B of Table 1.1, most of the performance pricing schemes (78%) are related to various accounting ratio, e.g., debt to EBITDA ratio. However, about 22.3% of performance pricing loans are linked to firms' debt rating. While debt ratings are generated based on many accounting variables, they are more difficult to be manipulated by managers than accounting ratios because credit ratings are synthesized by rating agencies, e.g., Moody's or Standard & Poor's. As such, we expect that conditional on using performance pricing loans, firms with poorer accounting quality would be more likely to use credit rating based performance pricing loans, while firms that have better accounting quality are more likely to use accounting based performance pricing loans.

To test the hypothesis above, we examine accounting quality affect the choice of accounting based versus rating based pricing measure. A selection problem arises because such a choice is observed only when a firm use performance pricing loan. Our Hausman test indicates that the choice of pricing scheme and the decision of using performance pricing are not independent. As a result, a binomial probit model that is estimated using only observations of performance pricing loans would yield inconsistent coefficient estimates. To address this problem, we estimate a Heckman probit model that takes into account sample selection that we observe accounting based or credit rating based pricing scheme only when performance pricing loan is used. The selection model of using performance pricing provision or not is estimated with the same variables as those in Table 1.5. In the probit model of the choice between accounting and credit rating based pricing scheme, we include firm characteristic and loan characteristic variables. Since rating based performance measure cannot be used unless a firm is rated by credit rating agencies, we include an additional rating dummy variable that equals one if any type of S&P debt rating is available from Compustat or Dealscan and zero otherwise.

Table 1.6 reports the results. We examine the effect of accounting quality on the choice of accounting based versus rating based performance pricing loans. The results of the selection model are presented in models (1) and (3). The coefficient estimates on both *Accrual measure* (DD_AQ10 and MDD_AQ10) are negative and significant at the 5% level. This result is consistent with our findings above: firms with poorer accounting quality are less likely to receive performance pricing loans (accounting based or rating based) than receiving non-performance pricing loans. The results of the probit model are reported in models (2) and (4) in which the choices of accounting based versus credit rating based performance pricing loan is evaluated. We find a significantly negative coefficient estimate on *Accrual measure* (DD_AQ10 and MDD_AQ10), suggesting that firms with lower accounting quality are less likely to receive accounting based performance pricing loans than receiving credit rating based performance pricing loans. The coefficient estimates on the strength of bank-borrower prior lending relation ($) are all positive and significant in the selection models as well as the probit models. It indicates that a stronger prior lending relation not only increases the likelihood for a borrower to obtain performance pricing loans, but also increases its probability of including an accounting based pricing provision rather than rating based.

In summary, we find that after controlling for many firm-specific and loan-specific characteristics, poorer (better) accounting quality is significantly related to the use of credit rating (accounting) based performance pricing loans.

5. Conclusion

In this study we examine how default risk, accounting quality of borrowers, and borrower-lender relation affect the choice of using performance pricing loans. We find that firms with poorer accounting quality are less likely to use performance pricing loans. Prior lending relation between a borrower and a lender could mitigate information asymmetry and enhance monitoring. We find that stronger borrower-lender relationship is associated with greater probability of issuing performance pricing loans.

To further examine the causality between accounting quality and the use of performance pricing provision, we investigate the change in the likelihood of performance pricing loans around financial restatement events. We find that the likelihood of receiving performance pricing loans is significantly reduced after financial restatements. Finally we evaluate the choice of using accounting based versus credit rating based performance measure, conditional on the decision of using performance pricing provision. We find that conditional on using performance pricing loans, firms with poorer (better) accounting quality are more likely to receive bank loans with rating (accounting) based performance pricing scheme.

Compared with previous research on performance pricing loans, our research makes the following contributions. We explore both the benefit and cost of using performance pricing loans, and we examine the effect of both borrowers' and lenders' characteristics as well as their relationship on the choice of using performance pricing loans. Related questions will be how the presence of performance pricing debts in firms' capital structure as well as the choice of using various performance measures affects the extent of accounting manipulation, conditional on the slack of firm's accounting performance. We will study these issues in future research, which would enhance our understanding in how debt contracting helps mitigating market friction.

CHAPTER 2

HOW COMMITTED ARE LINES OF CREDIT?
THE IMPACT OF LENDING RELATIONSHIP AND BANK REPUTATION

1. Introduction

Lines of credit or loan commitments are the most popular form of bank lending, representing 80% of commercial loans in the United States (Duca and Vanhoose 1990).[9] According to FDIC at the end of 2004 (www2.fdic.gov/SDI), outstanding unused lines of credit of U.S. corporation amount $1.7 trillion. Aggregate corporate cash holding for public firms are $1.67 trillion (sum of item 1 for all firms in Compustat) (Yun, 2009). Lines of credits are banks' promises for future lending sold to borrowers.[10] The borrower can draw down on the line of credit at any time prior to maturity, up to the maximum amount set in the agreement, and interest payments amounted according to the spread over LIBOR or prime rate (specified in the agreement) for each dollar drawn down. Once a borrower draws funds from a line of credit, this used portion becomes a debt obligation, which is formally recorded in a firm's balance sheet. The remaining unused portion of the line of credit stays available for future lending unless covenants are violated. The unused portion remains as off-balance sheet item.

Theoretical literature on corporate liquidity management considers lines of credit as a committed liquidity insurance to overcome capital market frictions. For example, prior studies have shown that lines of credit could mitigate asymmetric information problems between borrowers and lenders (Boot, Thakor, and Udell, 1987 and 1991) and resolve the

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[9] In the Dealscan data, 63% (or 73%)of loans are lines of credit based on the number of loans (or the amount of loans). These number increases to 82% (or 86%) in our sample that are present in Compustat and CRSP, and tend to be larger firms.

[10] To compensate banks for providing the optionality of immediate access to liquidity , borrowers usually pay a upfront fee as well as an annual commitment fee.

traditional underinvestment problem by imposing usage fees and maximum loan amounts (Berkovitch and Greenbaum, 1991). In addition, Holmstrom and Tirole (1998) and Tirole (2005) demonstrate that lines of credit could mitigate the moral hazard problem in which an entrepreneur will not exert effort unless he obtains a minimum share in the project value. Thakor (2005) explains why banks would avoid invoking the MAC clauses thereby declining to honor loan commitment too often because of their reputation concern.[11] If a bank declines to honor loan commitment too often, it will earn a bad reputation of not caring for its clients, which will adversely affect it banking business in the future.

In contrast to the extensive theoretical literature, empirical studies on the liquidity management role of lines of credit are limited. Sufi (2009) finds that firms with low cash flow are less likely to obtain a line of credit. Moreover, lines of credit are revoked when the firms' liquidity levels are low**.** His evidence suggests that lines of credit provide at most partial or contingent insurance. Campello, Giambona, Graham, and Harvey (2009) study corporate uses of lines of credit by public and private firms in the U.S. and abroad during the 2008-2009 financial crisis and document some similar findings as Sufi (2009). They find that more profitable firms have more access to lines of credit, especially in firms with low cash holdings. However, firms that are "credit constrained" (small, private, noninvestment grade, and unprofitable) draw down larger credit lines (as a proportion of assets) than their large, public, investment-grade, profitable counterparts. These studies suggest that banks provide credit lines that are contingent on maintenance of cash flow,

[11] Most loan commitment contracts include the Material Adverse Change (MAC) clause, which permits the bank to decline to lend under the commitment if the borrower's financial condition has declined significantly since the commitment was sold.

and lines of credit are therefore a poor liquidity substitute for firms that have low existing or expected cash flows. If the purpose of a line of credit is to insure firms against future liquidity shock, why it is taken away when a firm is actually experiencing one? Do lines of credit provide liquidity insurance at all?

Our paper tries to shed lights on the above questions empirically. Sufi (2009) and Campello, Giambona, Graham, and Harvey (2009) have been focusing on how firm characteristics are related to the amount of lines of credit available to the borrowers and the amount of their drawdown, and find that lines of credit at the best provide a contingent liquidity insurance. Nevertheless, even if a borrower is able to draw down a line of credit, it does not necessarily mean that the borrower is granted with an liquidity insurance, unless we observe that the drawdown rate on the line of credit is lower than the market rate the borrower could otherwise obtain from the lending market given its financial condition at the drawdown. An alternative hypothesis of using lines of credit is simply for convenience reason, just like consumers use credit card. Lines of credit might provide the convenience for firms to access funding quickly for investments or assets acquisition that are time limiting. Lins, Servaes, and Tufano (2008) analyze survey data collected from CFOs of public and private firms in 29 countries and document that 60% of firms view that lines of credit provide certainty of funding during event risk or acquisition opportunities, and 32% of firms indicate that the time to raise funds is an important consideration as they use lines of credit. The convenience hypothesis would suggest that the drawdown rate is the same as the market rate the borrower is able to obtain in the lending market at the time of drawdown. As a result, the key to test whether lines of credit provide liquidity insurance or convenience (conditional on the drawdown) is to investigate the drawdown rate.

This study is the first one that looks into the drawdown rate and analyzes whether the drawdown rate is different from the market rate, and what drives the difference. It is commonly assumed in the literature that the interest rate a borrower pays at the drawdown is predetermined in the lines of credit contract and will not change before the maturity date. Nevertheless there has been no studies directly analyzing the ex post drawdown rate. There are at least three reasons that the drawdown rate might be different from the initial loan spread specified in the contract at the origination. The first one is performance pricing, which is used extensively in lines of credit as a provision. The interest rate paid at drawdown in a performance priced line of credit will be Libor or prime rate plus a spread that are tied to borrowers' performance ex post. If a borrower's performance becomes poorer when it draws down a line of credit, the actual drawdown rate will be higher than the initial spread stated in the contract when the commitment was sold. The second reason that the drawdown rate might be different from the initial contract rate comes from covenant violation or technical default. Upon covenant violation, lenders would have the discretion to decline the loan commitment or renegotiate with the borrowers for a higher rate. Beneish and Press (1993) estimate that increased interest costs resulting from covenant violation range between 0.84 and 1.63 percent of the market share of sample firms' equity. The third reason is that, even in the absence of performance pricing and covenant violation, the drawdown rate might be different from the initial contract rate due to frequent renegotiation throughout the life of a loan contract. Roberts and Sufi (2009) show that over 90% of long-term debt contracts are renegotiated prior to their stated maturity. Renegotiation leads to significant changes the maturity, amount, and spread of the contract. Only fewer than 18% of the renegotiations are directly or indirectly linked to a covenant violation or payment default.

Furthermore, we examine the impact of prior lending relationship and bank reputation on how well banks honor their lines of credit. Research also demonstrates that relationship lending increases the precision of their information about the borrowers and lowers the cost of information production (Petersen and Rajan,1994; Berger and Udell, 1995). Therefore, compared to a new lender or a lender with weak prior lending relation, banks with strong prior lending relationship (close and continued interaction) with the borrowers would be able to monitor their financial and operating conditions more effectively (preemptive effect, so that borrowers are less likely to game the insurance policy), and more likely to make the “correct” revoking and pricing decisions as the borrowers intend to draw down their lines of credit. On the other hand, a bank's concern to maintain a "good" reputation can induce the bank to keep its commitment to a costly action (Boot, Greenbaum, and Thakor, 1993; Fudenberg and Levine, 1992; Chemmanur and Fulghieri, 1994). Therefore, bank reputation acts as a commitment device enabling banks to credibly promise borrowers that they will make better and more correct decisions in the event that borrowing firms is in financial distress or liquidity shock (Chemmanur and Fulghieri, 1994). As a result, we expect high reputation banks and banks with strong prior lending relationship would provide better liquidity insurance to borrowers ex post.

In this study, we examine 10-K filings for a randomly selected sample of 800 firms during 1996-2005 and retrieve detailed information of the facilities being drawn down and the actual drawdown rate. We find that the drawdown rate is on average significantly lower than the predicted market rate at the time of drawdown, suggesting that lines of credit do provide a liquidity insurance ex post by offering a lower rate. We find that borrowers are penalized (paying a higher spread and more likely pledging collateral on their new lines of credit) after they draw down their existing ones.

We find that stronger (or existence of) prior lending relation is associated with a lower drawdown rate, however bank reputation has no impact on that. Neither bank reputation nor prior lending relation affects the likelihood of drawing down upon borrowers' liquidity needs. Furthermore, we document that the impact of lending relation on the drawdown rate only exists in borrowers subject to greater information asymmetry. Finally, while firms are penalized (paying a higher spread and more likely pledging collateral on new lines of credit) after their drawdown, firms are penalized much less as they borrow from high reputation banks.

Our paper contributes to the existing literature as follows. First, to the best of our knowledge, this is the first empirical study documenting evidence on the actual drawdown rate. Secondly, this paper provides a direct test on the notion whether lines of credit provide any insurance at all. Thirdly, we shed light on how bank reputation and prior lending relation affect how well these lines of credit are honored ex post.

The rest of this paper proceeds as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 discusses data and methods. Section 4 presents empirical results and section 5 concludes the paper.

2. Literature Review and Hypotheses Development

2.1. Lines of Credit

Theoretical literature argues that lines of credit are committed liquidity insurance that could be used to overcome capital market frictions. Boot, Thakor, and Udell (1987) model an asymmetric information set up where the firm faces a liquidity shock. The line of credit serves as a put option for the firm to borrow at the pre-arranged low rate if the spot-market interest rates are high. The bank charges an ex-ante commitment fee to compensate for the loss. Berkovitch and Greenbaum (1991) show that a line of credit contract could resolve the traditional underinvestment problem under Myers' (1977) framework via imposing usage fees and maximum loan amounts in the contract. Holmstrom and Tirole (1998) and Tirole (2005) argue that a line of credit contract is adopted to mitigate the moral hazard problem in which an entrepreneur will not exert effort unless he obtains a minimum share in the project. In the three-stage model in Tirole (2005), a firm experiences a liquidity shock in the second period. This shock arises from a reinvestment need or from a shortfall in earnings at the intermediate stage, i.e. available resources are not enough to cover refinancing needs. One solution is to return to the capital market and issue new securities at the third period. Because of the existence of agency costs, the borrower must retain a large stake to motivate managers to be diligent, which prevents pledging the firm's full value to investors. If the liquidity shock is too large, the borrower cannot convince investors to renegotiate and let their claims to be diluted through a new security issue. An alternative solution is that the firm obtains a loan commitment in the first stage that allows it to borrow in the second stage up to a certain amount. This hoarding of reserves is viewed as an insurance mechanism that would guarantee firm's access to the capital as well as a lower rate (than what the firm can borrow in the spot market) so that the firm could pursue the NPV projects. In Tirole's model, a lower rate is a necessary condition. This is because if the firm is not allowed to draw down at a rate lower than the spot rate priced in new security issue, the loan commitment obtained would not be able to solve the moral hazard problem ex ante, and positive NPV project will be forgone. In return, firms pay an up-front fee to purchase the option of obtaining a lower rate of interest rate in the second stage.

Despite the well-established theoretical notion that lines of credit serve a fully committed liquidity insurance, there is limited empirical evidence supporting it. Lins, Servaes, and Tufano (2008) survey CFOs of public and private firms from 29 countries about aspects of corporate liquidity. They find that the median line of credit is equal to 15 percent of book assets whereas cash holdings comprise only 9 percent of book assets. Their results suggest that while cash holding is primarily held as a general buffer against future cash shortfalls, lines of credit, which represent options on liquidity, are strongly related to a firm's need for external financing to fund future investment opportunities. Sufi (2009) examines annual 10-K SEC filings, and obtains detailed information of the amount of lines of credit used or available to firms. He finds that firms with low cash flow are less likely to obtain a line of credit and the credit lines are revoked when the firms' liquidity levels are low**.** Firms with high level of cash flow rely on lines of credit, while firms with low level of cash flow rely on cash. Firms with low cash flow must maintain cash balances as a liquidity buffer because lines of credit may not be available when most needed. His results cast double on the theoretical notion that lines of credit are committed liquidity insurance.

Yun (2009) study how corporate governance influences firms' choices between cash and lines of credit, based on the premise of potential agency costs associated with cash holding. Self-interested management and/or controlling shareholders may use the cash to pursue personal benefits (e..g, personal perks or empire building) rather than to maximize shareholders' value. This is the typical free cash flow problem described in Jensen (1986). Yun finds that firms increase cash relative to lines of credit when the threat of takeover weakens (e.g., recent state adoption of antitakeover legislation increased the difficulty of successful takeover). This tendency is weaker for firms with good internal governance, e.g., the presence of large blockholders or institutional investors.

Campello, Giambona, Graham, and Harvey (2009) surveyed 800 CFOs regarding their liquidity management as well as their pro forma plans about investment, technology, and employment expenditures during the 2008-9 financial crisis. They find that profitability is important for firms to obtain or establish lines of credit, especially in firms with low cash holdings. Conditional on having access to lines of credit, firms that are small, private, low credit rating and unprofitable (constrained) draw more heavily on their lines of credit, at the same time that they are more likely to face difficulties in renewing or initiating lines of credit during the crisis. They also document that in the presence of low level of lines of credit, cash savings and investments competes for funding (negatively related). In firms with more cash savings, investment plans are boosted by greater access to lines of credit, suggesting that lines of credit seem to free up internal funds for investment when the firm has more options on external liquidity.

Recent empirical evidence suggests that lines of credit are at best a conditional insurance, which is contingent on borrowers' cash flow and liquidity position. Nevertheless prior empirical studies do not directly shed light on whether lines of credit provide insurance at all. Sufi (2009) and Campello, Giambona, Graham, and Harvey (2009) have been focusing on how firm characteristics are related to the amount of lines of credit available to the borrowers and the amount of their drawdown, and find that lines of credit at the best provide a contingent liquidity insurance. Nevertheless, even if a borrower is able to draw down a line of credit upon its liquidity need, it does not necessarily mean that the borrower is honored with an liquidity insurance, unless we observe that the drawdown rate on the line of credit is lower than the market rate the borrower could otherwise obtain from the lending market given its financial condition at the drawdown. An alternative hypothesis of using lines of credit is simply for convenience reason, just like consumers use credit card. Lines of credit might provide the convenience for firms to access funding quickly for investments or assets acquisition that are time limiting. Lins, Servaes, and Tufano (2008) analyze survey data collected for firms from 29 countries and document that 60% of firms view that lines of credit provide certainty of funding during event risk or acquisition opportunities, and 32% of firms indicate that the time to raise funds as an important consideration as they use lines of credit. The convenience hypothesis would suggest that the drawdown rate is the same as the market rate the borrower is able to obtain in the lending market at the time of drawdown. As a result, the key to test whether lines of credit provide liquidity insurance or convenience is to investigate the drawdown rate. Thus we have the following hypotheses:

*H2.1A: Drawdown rate is lower than the market rate the borrower is able to obtain in the lending market at the time of drawdown (*Insurance hypothesis).

H2.1B: Drawdown rate is the same (or a little higher than) the market rate the borrower is *able to obtain in the lending market at the time of drawdown (*Convenience hypothesis).

2.2. Lending Relationship and Bank Reputation on How Well Banks Honor Their Lines of Credit

Relationship banking has been viewed as a way to partly overcome capital market frictions and to lower financing costs for borrowers. In this study we are going to exam how lending relationship affect the likelihood and extent that banks honor loan commitments ex post.

As extensively studied in the insurance literature (e.g., Rothschild and Stiglitz, 1976), the insured may have moral hazard problem. More specifically, the firm being insured may take more risk than it should because it has guaranteed access to cheap financing. In order for lines of credit to add value, there have to be mechanisms to ensure, at least to some degree, that inefficient projects are not taken by the firm. Debt covenants and contract provisions are devices to mitigate the moral hazard problem. Nevertheless, contracts such as covenant, no matter how carefully written, are incomplete. That is, it is impossible to write down all the possibility of the future. As a result, when a firm is subject to significant change in financial condition or violates its covenants, it may reflect in some cases, the poor quality of its project; in other cases, it may be due to reasons unrelated to project quality (such as temporary industry and business shocks). In the former case the right course is for lenders not to honor the loan commitment; however, in the latter case it may be optimal for all parties to allow the firm to continue under a debt renegotiation arrangements, since the continuation value of the firm may be greater than its liquidation value.

Due to market friction, e.g., information asymmetry, lenders are unable to distinguish between the two kinds of situations without devoting significant resources to evaluate the firm. Hence bank monitoring plays an important role in this context. Existing literature (see, for example, Diamond, 1991; Petersen and Rajan,1994) has argued that through close and repeated interaction, relationship lending allows a bank to acquire through screening and monitoring proprietary information about, and a voice in, the firm's affairs, which results in increased precision of its information about the borrower as well as a lower cost in information production, since relationship lender could spread any fixed costs of producing information over multiple time period. Therefore the existence of a prior lending relation would be correlated with lower information opacity between the borrower and the lender. Prior studies have documented that lending relationships increase credit availability (see, for example, Petersen and Rajan, 1994), decrease loan rate and reliance on collateral (see, for example, Berger and Udell, 1995), and reduce the costs of financial distress (Hoshi, Kashyap, and Scharfstein, 1990). Berlin (1996) shows that a close relationship with a bank does increase the likelihood of successful renegotiation when a firm is in financial distress.

As a result, banks having stronger or closer relationship with the borrowers would be able to monitor the firm’s conditions more effectively that results in a preemptive effect so that borrowers are less likely to game the insurance policy, and more likely to make the “correct” revoking and pricing decisions accordingly. Due to the cost of monitoring and information production, a new lender or a lender with weak prior lending relation might simply decline to honor their lines of credit when borrowers are in financial difficulties so as to minimize their lending risk. Therefore, we propose the following hypothesis:

H2.2: Given all else equal, lenders will provide better insurance ex post to the borrower with which they have a stronger prior lending relationship.

More specifically, better insurance (a more efficient insurance contract) means that the bank will not revoke the line of credit as much when the firm's financial condition changes significantly. In addition, conditional on their granting of lines of credit, borrowers are allowed to draw down at a lower rate. As such, relationship lender will be more likely to honor loan commitments as the borrowers have a liquidity need, and allow borrowers to draw down at a lower rate.

While bank monitoring is essential to mitigate the moral hazard problem of borrowers in gaming the liquidity insurance contract, it also gives banks discretion in whether or not and at what rate they would honor the lines of credit. This inevitably subjects the bank to moral hazard problem as well. More specifically, the bank can revoke a firm’s line of credit or increasing the drawdown rate ex post, just as insurance companies may decline claims. This problem can be mitigated, however, if the lender and the borrower interact repeatedly. For example, a bank's concern to maintain a "good" reputation can induce the bank to keep its commitment to a costly action (see Boot, Greenbaum, and Thakor, 1993; Fudenberg and Levine, 1992; Chemmanur and Fulghieri, 1994). That is, if a bank declines to honor lines of credit too often, it will lose its reputation and thus will lose its clients and unable to charge a high price for its services in the future. Fudenberg and Levine (1992) argue that the long-run player (e.g., banks in the lending market) may choose to "invest in his reputation" by playing the strategy even when doing so incurs short-run costs, provided the costs are outweighed by the long-run benefit. Chemmanur and Fulghieri (1994) argue that bank reputation acts as a commitment device enabling banks to credibly promise borrowers that they will make better renegotiation decisions. Thus we have the following hypothesis:

H2.3: Given all else equal, more reputable banks will provide better insurance ex post.

As we discussed above, lending relationship and bank reputation could potentially mitigate information asymmetry and moral hazard problem in the insurance contracts. As a result, the effect of lending relationship and bank reputation would be larger for borrowers that are subject to greater information asymmetry, which is our next hypothesis:

H2.4: Given all else equal, the effect of lending relationship and bank reputation on the liquidity insurance ex post is greater for borrowers that are subject to greater information asymmetry.

Under the insurance hypothesis, a firm would draw down its line of credit only when its ex post financing cost is higher than the drawdown rate. To deter opportunistic drawdown behavior, banks might impose penalties after the drawdown as firms renew or obtain new lines of credit, e.g., a higher interest rate and/or commitment fees, more stringent contract terms. This is an analogy to the fact that insurance companies might raise premium after insured files a claim. On the other hand, we discuss above that strong prior lending relation would mitigate the moral hazard problem of insured via diligent monitoring (preemptive effect), thus strong lending relation would be associated with a smaller penalty for drawdown. In addition, frequent and severe penalties associated with drawdown would damage banks' reputation. As a result, high reputation banks would punish borrowers' drawdown to less extent. Based on these arguments, we have the following hypotheses:

H2.5: Given all else equal, borrowers are penalized by paying a higher rate and receiving more stringent contract terms on their new lines of credit after their drawdowns.

H2.6: Given all else equal, bank with strong prior lending relation and high reputation would penalize borrowers to less extent as they obtain new lines of credit after their drawdowns.

3. Data and Method

3.1. Data and Sample Construction

We first hand match all the borrower names in the Dealscan database during 1990-2007 with Compustat firm names. The Dealscan database contains detailed information on bank loans (including term loans and lines of credit) worldwide, such as borrower and lender identity, loan amount, LIBOR spread, issuing and maturity date, financial and general covenants, etc.[12] Among the list of matched firms between Dealscan and Compustat, we randomly selected 800 firms. We focus on only 800 firms because of the time involved in gathering and recording the information about drawing down lines of credit which is described below.

Through a variety of regulations, the SEC requires firms to file detail material debt agreements, sources of liquidity, and long-term debt schedules (Johnson, 1997; Kaplan and Zingales, 1997; Sufi, 2007; Nini, Smith and Sufi, 2007). For each of the 800

[12] About 60% of Dealscan data are collected from SEC filings, and the rest are obtained from direct contact with borrowers and lenders. According to Carey and Hrycay (1999), the Dealscan database covers between 50% and 75% commercial loans in the U.S. by 1992, and by 1995 it covers a greater fraction.

randomly selected firms, we look up 10-K filings at each fiscal year end during 1996-2005. Since we cannot find any 10-K filings for seven firms, we are left with 793 random firms.[13] From the 10-K filings, we gather information on whether there exist lines of credit, whether the credit facilities were drawdown and at what rate the credit facilities were drawn down. Information on whether the firm was out of compliance with any financial or general covenants was obtained from the web link http://faculty.chicagobooth.edu/amir.sufi/ (Nini, Smith, and Sufi, 2009). We end up with a panel of 6859 firm year observations. Since SEC does not require firms to report the exact drawdown rate of a line of credit, about 88.26% firm year observations did not state the exact drawdown rate though they indicate one or more lines of credit were drawn down. Firm specific variables are constructed using the Compustat/CRSP database.

To obtain detailed contract information regarding the credit facilities being drawn down, we try to match the credit facilities being drawn down as recorded in 10-Ks with the facilities recorded in the Dealscan database, based on starting date, maturity date, size of the facility, and lender information. However some firms did not offer enough information in the10-K filings that would allow us to determine which line of credit recorded in Dealscan was drawn down. As a result, we do not have any contract information about these credit facilities, e.g., maturity date, initial spread, etc. Finally we obtain only 804 observations with both drawdown rate available from 10-K and detailed contract information of the line of credit available from the Dealscan.[14] All facility specific variables are obtained from the Dealscan database.

[13] While most of drawdown rate were expressed in spread over LIBOR rate, some were reported as a percentage of return. For these cases we use the corresponding LIBOR rates to impute drawdown spread.

[14] Some observations represent multiple drawdown of the same facility. The drawdown sample consists of 456 facilities issued by 257 firms.

3.2. Predicted Drawdown Rate

Based on Tirole (2005), lines of credit would provide insurance to firms, i.e., the drawdown rate would be lower than “the fair market rate” the firm is otherwise able to obtain from the lending market. To test the "Insurance" hypothesis, we compare the actual drawdown rate with the “the fair market rate.” Unfortunately “the fair market rate” is unobservable, hence we follow Graham, Li and Qiu (2008) and employ the following model to impute a bank loan rate given a firm’s financial condition at the time of drawdown:

Loan spread = Drawdown dummy+ Covenant violation dummy+ Log(asset)
+ Market-to-book + Leverage + ROA + Tangibility+ Cash flow volatility
+ Zscore + Log(maturity) + Log(loan size) + Performance pricing dummy
+ Security dummy + Loan type dummies + Loan purpose dummies
+ Credit spread + Term spread +Year dummies + Industry dummies.

(2.1)

In the model, we regress loan spread on a set of firm-specific and loan-specific variables used in Graham, Li and Qiu (2008). In addition, we include in the above equation two dummy variables for drawdown and covenant violation to capture the private information associated with a firm's decision of drawing down the lines of credit as well as whether a firm is in compliance with debt covenants. Loan spread is the loan price at the issuance, which is the Dealscan data item all-in-spread-drawn. Drawdown is a dummy variable that equals one if a firm draws down in one or more credit facility in a particular year, and zero otherwise. Covenants violation is a dummy variable that equals one if a firm violates its debt covenants in a particular year, and zero otherwise. All other variables are as defined in Appendix B.

We first estimate the above model using all the bank loans issued by the 793 sample firms during 1996 and 2006, and obtain coefficient estimates of all the variables.[15] For each drawdown event, we compute an "imputed" loan spread based on the coefficient estimates and the loan-specific variables of the facility being drawn down as well as the firm-specific variables at the time of drawdown. This "imputed" rate could be thought as the "fair market rate" a firm could otherwise obtain in the lending market, given its financial condition at the drawdown. We call this "imputed" loan spread as "predicted market rate." The difference between the drawdown rate and the predicted rate is considered as the drawdown rate benefit.

3.3. Regression Model

In the paper, we are interested in two related questions: How lending relationship and bank reputation affect the likelihood of granting a drawdown of the line of credit upon borrowers' liquidity need? Conditional on the drawdown, how lending relationship and bank reputation affect the drawdown rate benefit? Since the choice of drawing down is likely to be correlated with the rate benefit, we adopt the Heckman's (1979) two-stage procedure to model these two questions as follows.

$$\begin{aligned} \textit{Drawdown dummy} &= \textit{Bank reputation (or Lending relation)} + \textit{Cashflow} + \textit{Cash holding} \\ &+ \textit{Cashflow*Cash holding} + \textit{Large firm} + \textit{Investment grade} \\ &+ \textit{Market-to-book}, \end{aligned}$$

(2.2A)

[15] Ideally we would like to estimate the above loan pricing model use all the bank loans of all the firms recorded in Dealscan, however we do not have information on whether a firm is drawing down its credit facility except the 793 randomly select firms.

$$\begin{aligned}\textit{Drawdown rate} - \textit{Predicted market rate} \\ &= \textit{Bank reputation (or Lending relation)} + \textit{Covenant violation dummy} \\ &+ \textit{First Drawdown dummy} + \textit{Log(asset)} + \textit{Market-to-book} + \textit{Leverage} + \textit{ROA} \\ &+ \textit{Tangibility} + \textit{Zscore} + \textit{Log(loan maturity)} + \textit{Log(loan size)} \\ &+ \textit{Performance pricing dummy} + \textit{Loan type dummies} + \textit{Loan purpose dummies} \\ &+ \textit{Industry dummies} + \textit{Inverse Mills Ratios.}\end{aligned}$$

(2.2B)

In equation (2.2A) that explains the choice of drawdown, we follow Campello et al. (2009) and include firm-specific variables like cash flow, cash holding, the interaction term between cash flow and cash holding, a large firm dummy for firms with net sales of at least $1 billion, an investment grade dummy, and market to book ratio for investment opportunities. Please see Appendix A for details on variable definitions. In addition to these variables that capture firms' demand of drawing down their lines of credit, we include variables proxy for bank reputation and prior lending relation in equation (2.2A) to examine their impact on the likelihood of drawdown. In equation (2.2B), we follow Graham, Li and Qiu (2008) and include many firm-specific and loan-specific variables in explaining the drawdown rate benefit (drawdown rate - predicted market rate). Bank reputation and prior lending relation are also included in equation (2.2B) to examine their direct impact on the rate benefit in addition to their effect on the probability of drawdown. In addition, we include the inverse mills ratio from equation (2.2B) to correct for any potential selection bias resulted from the drawdown decision.

3.4. Measures of Bank Reputation and Lending Relation

Our analysis on bank reputation and prior lending relation focuses on lead arrangers.[16] Following Sufi (2007), we classify lenders listed in “Lender-Lead Arranger” as lead arranger if this variable is available from the custom report of Dealscan. Otherwise, we classify lenders having a “lead role” listed in “Lenders-All lenders” as the lead arranger. To make data collection manageable, we focus on the top 100 lead arrangers in Sufi (2007). This selection will not result in any bias, because according to Sufi (2007), the top 100 lenders represent about 96% of the total number of loans. To take into account bank mergers during our sample period, we track all mergers and acquisitions of financial institutions, and allow the acquiring banks to inherit all the lending history of the acquired bank after the acquisition date. For example, in April 1998, First Union Corp. acquired CoreStates Financial Corp. with a name of merged entity ‘First Union Corp.’ Thus after April 1998, First Union Corp. inherited CoreStates’ entire lending history as we compute lender market share and lead bank-borrower relation.

Following previous literature (e.g., Bharath, Dahiya, Saunders, and Srinivasan, 2007), we use a lead arranger’s market share in lending in the previous five years as a proxy for lead arranger’s reputation. It is computed as the dollar amount of loans arranged by a particular lead bank during the previous 5 years divided by the total amount of loans issued in the market in the same period.[17] Prior lending relation is computed as the fraction of all loans issued by a particular borrower during the previous 5 years that were arranged by a particular bank. Specifically, for a borrower j in a particular year, the amount of loans arranged by bank i and its predecessors during the

[16] While most of loans in Dealscan involve several lenders, it is the lead arrangers’ responsibility to negotiate directly with the borrower for all contract terms. Participant lenders rarely directly negotiate with the borrowing firm and usually hold a relatively small share of the loan.

[17] We also constructed lend arranger’s market share in previous year as a proxy for lender’s reputation, and obtained similar results.

previous 5 years divided by the total amount of loans borrowed by borrower j during the same period. While this measure of relation captures the intensity of lending, we also construct an alternative measure that focuses on the existence of a prior lending relation. It is a dummy variable that is equal to one if a particular bank has lent as a lead arranger to a particular borrower during the previous 5 years. According to H2.2 and H2.3, we expect that prior lending relationship and bank reputation is positively related to the likelihood of drawdown, and negatively related to the drawdown rate.

4. Empirical Results

4.1. Sample Statistics

We present summary statistics of our sample in Table 2.1. Our starting sample consists of a total of 793 randomly selected companies during 1996 to 2005. About 83% of total firm-year observations have a line of credit, and 53% of them are associated with a drawdown.[18] The mean value of covenant violation dummy indicates that about 7% of the observations are associated with a covenant violation. Average firm assets size is $1.5 billion, while the median assets size is smaller, $277 millions. Average leverage ratio of our sample firms is 0.24, average market-to-book ratio is 1.9, and average ROA is 0.097.

4.2. Univariate Analysis

Table 2.2 presents univariate analysis of a sample of credit facilities for which we are able to identify the drawdown rate from the 10K filings. As shown in panel A, we are

[18] Out of those 793 companies, 750 companies (94.58%) have obtained at least one line of credit during the sample period, while 43 companies do not have any line of credit. 647 firms (86.27%) drew down their lines of credit at least once, and the other 103 companies never drew down any lines of credit in the entire sample period.

able to identify 804 drawdown rates related to 456 facilities being drawn down by 257 companies. The mean (median) contract rate on these lines of credit that were subsequently drawn down is 175 (150) basis points over LIBOR, which is lower than the mean (median) of the actual drawdown rates reported in 10Ks. Predicted market rate is an imputed rate based on the regression model (Graham, Li and Qiu, 2008), given the financial condition of the borrowers at the time of drawdown. The mean (median) predicted rate is 223 (222) basis points over the LIBOR rate, which appear higher than the mean (median) drawdown rate. We also identify the first new line of credit initiated after each drawdown, and the average contract rate on these new facilities is 177 basis points over the LIBOR rate.[19]

In panel B, we compare the actual drawdown rate and the predicted market rate, which proxies for "fair market rate" the firm is able to obtain from the lending market at the time of drawdown. We find that drawdown rate is 25.05 (40.85) basis points lower than the predicted market rate as we examine the mean (median) difference, and the result are statistically significant at 1% level. This evidence supports the insurance hypothesis that lines of credit on average do provide a lower rate when borrowers have liquidity needs. As we compare the drawdown rate with the contract rate on the line of credit being drawn down, the mean difference is 21 basis points and highly significant, however the median difference is not statistically significant. Hence we find some evidence that the actual drawdown rates are on average higher than the initial contract rate specified at the time when the lines of credit were set up.

[19] Since some borrowers have not obtained any new line of credit after the drawdown, we have only 631 observations on contract rate of new line of credit.

In addition, we compare the drawdown rate and the contract rate on new lines of credit started after the drawdown. The insurance hypothesis suggests that the drawdown rate would be lower than the new contract rate specified after the drawdown, assuming that the borrowers' financial conditions stay the same between the drawdown and the new contract date. As shown in Panel B of Table 2.2, the mean and median difference between the drawdown rate and the new contract rate after are both positive however insignificant. It is noteworthy that we might have selection problem that would bias our results against finding the insurance effect. This is because whether and how soon the borrowers are able to obtain new lines of credit are endogeneous. Borrowers are more likely to receive a new credit facility if their financial conditions improve after the drawdown, therefore our observed rates on new line of credit rate tend to be lower than the TRUE spot rates that borrowers are facing after the drawdown.

4.3. Bank Reputation, Lending Relationship, and Drawdown Rate

As we argued above in developing our hypotheses $H_{2.2}$ and $H_{2.3}$, due to their information and monitoring advantages and reputation concern, banks stronger prior lending relationship and with higher reputation would be more likely to honor their commitments and grant a better liquidity insurance ex post (i.e., a lower drawdown rate). To test hypotheses, we first examine in a univariate test how the drawdown rate benefit (drawdown rate minus predicted market rate) is related to bank reputation and prior lending relationship. As shown in Table 2.3, we divide the whole sample into two groups based on the median value of bank reputation or strength of prior lending relation between the bank and the borrower, or the existence of a prior lending relation. The mean and median difference between drawdown rate and the predicted market rate are both negative and significant regardless high or low bank reputation. Moreover, the drawdown rate benefit is not significantly different between the two groups of banks with high and low reputation. These results suggest that bank reputation does not affect the drawdown rate, which is not consistent with our hypothesis $H_{2.3}$.

As we divide our sample into strong and weak prior lending relation, we find that the difference between drawdown rate and the predicted market rate is significantly negative but only in the subsample with strong prior lending relation. In this group the drawdown rate is on average 62.6 basis points lower than the predicted market rate. In contrast, as firms borrow from banks with a weak prior lending relation, the drawdown rate is not significantly different from the predicted market rate. The difference between the two groups with strong and weak lending relation is negative and highly significant. In addition, we obtain similar results when we divide the sample into two groups, one with and another without any prior lending relation. Again drawdown rate is significantly lower than the predicted market rate, but only in the subsample with the existence of a prior lending relation. These results support the hypothesis H_2 in that lenders offer a lower drawdown rate for borrowers with which they have a stronger prior lending relation.

Since the choice of drawdown as well as the drawdown rate might be jointly determined by many firm-specific and contract-specific variables, we will next examine H_2 and H_3 in a multiple regression framework. We estimate equation (2.2A) and (2.2B) using the Heckman's (1979) two-stage procedure. The Heckman model is estimated based on a sample of firm year observations with lines of credit available. Both observations with and without a drawdown are included. However, to be included in the estimation, an observation without a drawdown must have non-missing value in all of the independent variables in equation (2.2A). An observation with a drawdown must have non-missing value in drawdown rate, predicted market rate, and all of the independent variables in both equation (2.2A) and (2.2B). As a result, we are left with about 1,200 firm year observations. The estimation results are reported in Panel A and B for equation (2.2A) and (2.2B) respectively in Table 2.4.

In Panel A, we examine how bank reputation and prior lending relation affect the likelihood of drawing down lines of credit. Since we focuses on the supply side, i.e., how likely banks would honor their loan commitments, we must control for the demand side, i.e., how much borrowers would like to draw down. We follow Campello et al. (2009) to model the demand for drawdown by including many firm-specific variables. We find that cash flow is not significantly related to the likelihood of drawdown. However the interaction term between cash flow and cash holding is negative and highly significant. It implies that while cash flow does not affect the decision of drawdown in the absence of any internal cash (or with low level of cash holding), in the presence of high level of internal cashes, borrowers with lower cash flow are more likely to draw down their lines of credit. In addition, cash holding is significantly negatively related to drawdown, suggesting a substitution effect between cash holding (internal liquidity) and drawing down lines of credit (external liquidity).[20] The significant negative coefficient on the interaction term of cash flow and cash holding indicates that the substitution effect is even stronger in firms with greater cash flow. This result is consistent with the findings

[20] Campello et al. (2009) also document a significant negative relationship between cash holding (as well as cash flow) and the amount of drawdown during the 2008-9 financial crisis.

documented in Sufi (2009) and Campello et al. (2009), suggesting a conditional insurance effect: lines of credit are better liquidity substitute for firms that are more profitable. As with Campello et al. (2009), we find that large firms are less likely to draw down, since they in general have better liquidity than small firms. Neither firms' rating (Investment grade dummy) nor the market-to-book ratio is significantly related to the likelihood of drawdown. Given that market-to-book ratio proxies for investment growth prospects, we find no evidence on the argument that drawdown on lines of credit is related to firms' need for financing future investment opportunities as suggested in Lins, Servaes, and Tufano (2008).

After we control for the demand for drawdown, neither high bank reputation nor strong lending relation is significantly related to the probability of drawdown (see model (1) and (2)). The coefficient estimate on the existence of prior lending relation as reported in model (3) is negative however only marginally significant at the 10% level. In model (4) we include dummy variables for both bank reputation and strong lending relation in the same model, and obtain similar result. These findings suggest that bank reputation and prior lending relation do not affect the probability of banks honoring their loan commitments.

It is noteworthy that the match between banks and borrowers is not random, instead it might be determined by certain characteristics of the borrowers. For example, Dinc (2000) develops a theory and shows that higher reputation banks would offer loans with commitment to the highest quality borrowers, however an increase in credit market competition enhances banks’ incentive to lend to borrowers in distress. As a result, the effect of bank reputation and prior lending relation on the likelihood of drawdown or drawdown rate (as we will discuss next) might be driven by certain borrowers' characteristics that would affect the demand side of drawdown or drawdown rate. To address the endogenous choice between borrowers and banks, we employ a two step instrumental variable approach. We follow Bharath et al. (2007) and include firm size, ROA, asset tangibility, and a dummy for accessing public debt market as instruments.[21] The results that correct for the endogeneity issue are reported in model (5) and (6). As with what we find above, neither bank reputation nor lending relation is significantly related to the probability of drawdown.

In Panel B, we examine that conditional on the drawdown, how bank reputation and prior lending relation affect the drawdown rate benefit. The dependent variable in Panel B is the rate benefit, i.e., the drawdown rate minus the predicted market rate. The more negative is the dependent variable, the greater the rate benefit. After controlling for many firm-specific and contract-specific variables, model (1) shows that high bank reputation dummy is not significantly related to the rate benefit. As shown in model (2) and (3), strong lending relation dummy and a dummy for the existence of prior lending relation however are associated with a significant greater rate benefit of 54 and 55 basis points, respectively. Put another way, relationship banks would allow their borrowers to drawdown lines of credit at 55 basis points lower than non-relationship banks. As we include both bank reputation and lending relation variable in model (4), high bank reputation dummy remains positive and insignificant, whereas strong lending relation dummy is still negative and highly significant. In model (5) and (6), we obtain similar results after we account for the endogeneity choice between banks and borrowers. In

[21] We define that a firm has access to the public debt market if any type of S&P debt rating is available in the Compustat database.

summary, we find support for our hypothesis $H_{2.2}$: strong prior lending relation between banks and borrowers results in a significantly lower drawdown rate. Therefore, banks appear providing a better liquidity insurance ex post to borrowers with which they have a strong prior lending relation. Nevertheless, we do not find evidence that strong lending relation leads to high probability for banks to honor their loan commitments.

As for the control variables, covenant violation is associated with a significant increase of drawdown rate by more than 30 basis points. The coefficient estimate on first drawdown dummy is insignificant, suggesting that drawdown rate is not different between the first drawdown and subsequent drawdowns. While more profitable borrowers (high ROA) pay a lower drawdown rate, borrowers with higher leverage are required to pay a higher rate. Other firm characteristics variables are insignificant. In addition, larger loan size and longer time to maturity of the line of credit contracts are associated with significant higher drawdown rate. The coefficient estimates on the inverse mills ratio are all positive but insignificant, suggesting that sample election bias is not a major concern for our analysis.

As we discussed in section 2, lending relationship and bank reputation could potentially mitigate information asymmetry and moral hazard problem in the insurance contracts. As a result, the effect of lending relationship and bank reputation would be larger for borrowers that are subject to greater uncertainty and information asymmetry, as suggested in our hypothesis $H_{2.4}$. If there is no or minimum degree of information asymmetry, lending relationship and bank reputation would play little role in how likely and how well a liquidity insurance will be honor. To examine hypothesis $H_{2.4}$, we introduce two measures of uncertainty and information asymmetry and their interaction terms with the bank variables. The first one follows Sufi (2009), is a dummy variable for no access to public debt market (No public debt dummy), which is equal to one if a firm does not have any type of S&P debt rating available in the Compustat database, and zero otherwise. The second one is a high return volatility dummy that is equal to one for firms with stock return volatility above the sample median. High return volatility would suggest high uncertainty and greater information asymmetry, for which the advantages in monitoring and information production due to reputation concern and relationship lending are expected to be greater. The interaction term, e.g., Strong lending relation*No public debt would capture the differential effect of lending relation between borrowers with and without access to public debt market. Our proposition suggests that the coefficient estimate on the interaction term would be significantly negative.

Table 2.5 presents the Heckman two-stages model including the interaction terms. In Panel A, we model the choice of drawdown or not. As with Panel A of Table 2.4, the coefficient estimate on high bank reputation dummy is insignificant in model (1) and (2). As expected, no public debt dummy itself is significantly positively related to the likelihood of drawdown. This is because firms without access to public debt market are more likely to be financially constrained, which will then lead to frequent drawdown of their lines of credit. However high return volatility dummy is not significantly related to the probability of drawdown. Neither of the interaction terms, High bank reputation*No public debt or High bank reputation*High return volatility is significant. Model (3) and (4) show that the strong lending relation is not significantly related to the likelihood of drawdown, regardless whether borrowers face more or less severe information asymmetry. In summary, bank reputation and prior lending relation do not affect banks' probability to honor their loan commitments, even for borrowers face greater information asymmetry.

In Panel B, we explore the potential differential impact of bank characteristics on drawdown rate benefit in firms with greater or smaller extent of information asymmetry. As shown in model (1) and (2), high bank reputation dummy is not significantly related to the rate benefit. While the dummy for no public debt is insignificant, high return volatility is significantly and positively related to the difference between the drawdown rate and the predicted market rate, suggesting a smaller rate benefit. Again neither of the interaction terms, High bank reputation*No public debt or High bank reputation*High return volatility is significant. Thus bank reputation does not affect the rate benefit conditional on the drawdown, regardless firms with high or low information asymmetry. As we examine the impact of lending relation in model (3) and (4), we find that the coefficient estimate on strong lending relation dummy becomes insignificant as we add two additional variables: No public debt dummy (or High return volatility dummy) and their interaction terms with strong lending relation dummy. Most interestingly, both interaction terms, Strong lending relation*No public debt and Strong lending relation *High return volatility are negative and significant in model (3) and (4), respectively. These results indicate that for borrowers face low level of information asymmetry, strong prior lending relation has no significant effect on the insurance benefit (a lower drawdown rate than the fair market rate). In contrast, for borrower with greater information symmetry, strong prior lending relation is associated with a significantly lower difference in the drawdown rate and the predicted market rate (i.e., a higher rate benefit upon the drawdown). This result is consistent with our hypothesis $H_{2.4}$ that the impact of prior lending relation is greater for borrowers subject to more severe information asymmetry, since relationship lending would mitigate the information problem.

4.4. Any Penalty After the Drawdown of Lines of Credit?

Under the insurance hypothesis, a firm would draw down its line of credit only when its ex post financing cost is higher than the drawdown rate. To mitigate the opportunistic drawdown behavior, banks would impose penalties after the drawdown as borrowers renew or obtain new lines of credit. Penalties could take forms of a higher interest rate and/or commitment fees, more stringent contract terms, etc. In this section, we will test hypothesis H_5 and H_6 on whether there exist any penalty associated with a drawdown, and how bank reputation and prior lending relation affect the penalty. For this purpose, we take all the drawdown events and identify all the lines of credit contracts that were issued before and after each drawdown events. We will examine how the loan rates and other non-price terms of the lines of credit (e.g., time to maturity, collateral) change before versus after the drawdown, after controlling for borrowers' financial conditions.

We only keep the first drawdown if a firm draws down its line of credit more than once, which leaves us 2,065 credit facilities issued by 345 companies.[22] Sample statistics are reported in Table 6. There are 705 credit facilities issued before drawdown and the rest (1360) issued after the drawdown.[23] The mean and median of loan spread specified in these lines of credit contract are 155 and 125 basis points, respectively. Secured

[22] We keep the first drawdown for each firm because we aim to examine the change of loan terms before and after drawdown events, and the post-drawdown window of the first drawdown is likely to overlap with the pre-drawdown window of second drawdown. This would be problematic in interpreting the results.
[23] To be included in our sample, we require a firm to have at least one line of credit issued before and after the drawdown.

dummy is equal to one if a line of credit is secured (i.e., contain a collateral), and zero otherwise. The mean secured dummy indicates that about 67% of facilities include a collateral. On average these facilities include 1.37 and 2.81 financial and general covenants, respectively. Average time to maturity of these lines of credit is 43 months (3.6 years), with an average size of $250 million. About 45% of these facilities contains the performance pricing provision. While we are interested in examining the change in upfront fees and annual fees, there are less than 20% of facility contracts containing information on these fees, which prevents us from obtaining any meaningful results.[24]

To examine the effect of drawdown events on contract terms of lines of credit that are issued before and after the drawdown, we estimate the following regression model:

$$Loan\ contract\ term = \alpha_1 + \beta_1 Post\text{-}\ drawdown + \sum_i \gamma_i Control\ variables_{t\text{-}1} + \varepsilon_t . \quad (2.3)$$

In equation (2.3), *Post-drawdown* is a dummy variable which equals one if a line of credit is initiated after the firm draws down its existing line of credit for the first time during our sample period. This key variable will capture the change in facility contract terms attributed to the drawdown events after we control for the change in firm- and contract-specific characteristics. Our analysis above indicates that lines of credit provide insurance at the time of drawdown. Next we are going to examine whether and how lenders penalize borrowers when they obtain new lines of credit after the drawdown. Since penalty could take many forms, we will examine both loan price (spread) and non-price terms (time to maturity, collateral) of lines of credit before and after a drawdown.

Table 2.7 presents results of multiple regressions that examine the effect of

[24] We examined the effect of drawdown on upfront fee and annual commitment fee based on a small sample of 381 observations with which these fees are available, and did not find any significant results.

drawdown events on loan price and non-price contract terms of lines of credit. In model (1), we estimate an OLS regression with Log(loan spread) as the dependent variable. The coefficient estimate of *Post-drawdown* is positive and statistically significant. Based on the magnitude of the coefficient estimate, spread of lines of credit increases by 27.07 basis points after drawdown compared to before the drawdown events, holding all other variables at their median values. It suggests that compared to lines of credit issued before the drawdown event, borrowers must pay a significant higher interest rate on the lines of credit they obtain after the drawdown. Model (2) presents results of an OLS regression explaining the logarithm of the time to maturity of these lines of credit. We find that time to maturity decreases after the drawdown, however the result is not statistically significant. In model (3) we estimate a Probit model with the secured dummy as the dependent variable. The coefficient estimate on *Post-drawdown* is positive and significant at 1% level, suggesting that the likelihood of including a collateral in a new line of credit significantly increases after a firm draws down its existing facility. Based on the coefficient estimate of *Post-drawdown*, we find that holding all other variables at their mean values, borrowers are 15.73% more likely to pledge a collateral on new lines of credit issued after the drawdown compared to the facilities before the drawdown.

In general, our results show that after borrowing firms draw down their lines of credit, they pay a significantly higher loan spread and are more likely to pledge a collateral on the new lines of credit. However maturities of these new facilities are not significantly shortened. These results suggest that firms are punished after they draw down their lines of credit.

4.5. Bank Reputation, Lending Relationship, and the Penalty After the Drawdown

We document above that firms get punished after they draw down lines of credit. Next we will examine whether bank reputation and prior lending relation would mitigate the penalty associated with the drawdown, as suggested in our hypothesis $H_{2.6}$. For that purpose, we include a High bank reputation dummy (or Strong lending relation dummy) and its interaction with *Post-drawdown* in the regression models as shown below:

$$\begin{aligned} Loan\ contract\ terms &= \alpha_1 + \beta_1 High\ bank\ reputation + \beta_2 Post\text{-}drawdown \\ &+ \beta_3 High\ bank\ reputation{*}Post\text{-}drawdown + \sum_i \gamma_i Control\ variables_{t-1} + \varepsilon_t, \end{aligned} \tag{2.4}$$

$$\begin{aligned} Loan\ contract\ terms &= \alpha_1 + \beta_1 Strong\ lending\ relation + \beta_2 Post\text{-}drawdown \\ &+ \beta_3 Strong\ lending\ relation{*}Post\text{-}drawdown + \sum_i \gamma_i Control\ variables_{t-1} + \varepsilon_t. \end{aligned} \tag{2.5}$$

In equation (2.4) or (2.5), β_2 captures the effect of drawdown on contract terms for banks with low reputation or weak prior lending relationship, respectively. The impact of drawdown for banks with high reputation or strong prior lending relationship is captured by $\beta_2 + \beta_3$ in equation (2.4) or (2.5) respectively, while β_3 measures the differential effect of drawdown on contract terms between high versus low bank reputation, or strong versus weak lending relation.

Table 2.8 reports the results of multiple regressions as shown in equation (2.4) and (2.5). In model (1), the coefficient estimate of *Post-drawdown* is positive and significant, suggesting that as borrowers work with low reputation banks, loan spread on newly issued credit facilities rises significantly after the borrowers take down their existing lines of credit. However the coefficient estimate of *High bank reputation*Post-drawdown* is negative and significant, leading to an insignificant coefficient estimate of $\beta_2 + \beta_3$. This result indicates that as firms borrow from high reputation banks, they need not pay a higher loan spread on new credit facilities issued after a drawdown. In model (2), the coefficient estimate of β_3 is insignificant, suggesting no significant differential effect of drawdown associated with strong versus weak lending relation. In model (3) and (4), we again find no significant effect of drawdown on the time to maturity of newly issued lines of credit, and no differential effect related to bank reputation and lending relation. Model (5) shows that credit facilities issued after the drawdown are more likely to include collaterals, however only as the facilities are from low reputation banks. In borrowers that work with high reputation banks, the impact of drawdown on the likelihood of including collaterals becomes insignificant, as reflected in the coefficient estimate of $\beta_2 + \beta_3$. In contrast, the effect of drawdown on the probability of including collaterals is not different in banks with strong versus weak prior lending relation.

In summary, we find evidence supporting hypothesis $H_{2.6}$ that high bank reputation are less likely to penalize borrowers or penalize them to less extent after they draw down their existing lines of credit. Nevertheless prior lending relation seems not help mitigate the penalty caused by drawdown.

5. Conclusion

In this study we examine whether lines of credit provide liquidity insurance to firms during financial deterioration, and we also examine the impact of prior lending relationship and bank reputation on how well banks honor their lines of credit. We find that drawdown rate is on average significantly lower than the imputed market rate on a bank loan given the financial condition of a firm at the time of drawdown, which supports the theoretical notion that lines of credit offer liquidity insurance. In addition, we document that stronger (or existence of) prior lending relation is associated with a lower drawdown rate; however bank reputation has no impact on the drawdown rate. Furthermore, we find that the impact of lending relation on the drawdown rate only exists in borrowers subject to greater information asymmetry.

Our results suggest that lines of credit provide liquidity insurance at the time of drawdown. But lenders may penalize firms after firms draw down lines of credit, i.e. when they obtain new lines of credit. To further test the insurance hypothesis after a drawdown, we examine both price (interest) and non-price terms of new lines of credit. We find that while firms are penalized (paying a higher spread and more likely pledging collateral on new lines of credit) after their drawdown, firms are penalized much less as they borrow from high reputation banks.

Compared with previous research on lines of credit, our research makes the following contributions. To the best of our knowledge, this is the first empirical study documenting evidence on the actual drawdown rate. This paper provides a direct test on the notion whether lines of credit provide any insurance at all. We also shed light on how bank reputation and prior lending relation affect how well these lines of credit are honored ex post. Related questions will be how the ratio of used credit lines and total amount of credit lines affect the drawdown rate. We expect that using 1% of total amount of credit lines will have different effect on drawdown rate from using 100% of total amount of credit lines. We will study these issues in future research.

CHAPTER 3

PERFORMANCE PRICING DEBTS AND EARNINGS MANAGEMENT

1. Introduction

Performance pricing is a relatively new provision in bank loan contracts. Different from traditional bank loans, interest rate on performance pricing loans are based on LIBOR or prime rate plus a spread tied to borrowers' performance, e.g., credit rating or financial ratios like debt-to-EBITDA ratio. A typical performance pricing loan charges lower (higher) interest rates as borrower's performance becomes better (poorer). Performance pricing loans become more important in the last two decades. My Essay 1 (2010) documents that about 1% of all bank loans were performance priced in 1991 and this number goes up to 49% in 2006.

Since interest rates of performance pricing loans changes with firm's performance, it creates an incentive for firm's managers manipulate earnings so as to achieve a lower cost of debt. This argument is in the same spirit as the positive accounting theory (Watts and Zimmerman, 1986, 1990), which suggests that managers have the incentive to change accounting method or make financial reporting decisions that reduce the likelihood of violating accounting-based covenants in debt contracts. DeFond and Jiambalvo (1994) find that abnormal accruals are positive and significant in the year prior to debt covenant violation.

Compared to covenants under which managing accounting information provide benefits to the borrower when the firm is close to violating covenant constraints, performance pricing provide a more continuous and direct link between accounting information and interest rates. Therefore, it is likely that performance pricing gives managers additional incentives to manage accounting information, even when the firms are in compliance with debt covenants. My Chapter 1 (2010) shows that a manager's incentive to manipulate earning is indeed a determinant for whether a firm is able to obtain a performance pricing loan. Firms with poorer accounting quality are less likely to receive performance pricing loans. Using financial restatement as a proxy for financial reporting quality, I find that the likelihood of receiving performance pricing loans is significantly reduced after borrowers' accounting quality deteriorates, e.g., after they restate their financial reports.

In this study, we aim to address the following question: Do performance pricing loans encourage managers to manipulate earnings more aggressively? In particularly, we examine how the slope and convexity of the performance pricing schedule affect discretionary accruals. Steeper and more convex pricing schedule imply a larger decrease (increase) of interest rate given a fixed degree of firms' performance improvement (deterioration). Therefore, a steeper and more convex pricing schedule offers greater benefit for managing earnings to the same degree, which hence provides a higher incentive for managers to manipulate earnings. We follow Tchistyi, Yermack and Yun (2007) to compute slope and convexity of the performance pricing schedule of each loan, and non-performance pricing loans have slope and convexity of zero. After obtaining slope and convexity of each loan, we aggregate dollar weighted average slope or convexity for each firm in every year to examine the relation between slope/convexity and firm's discretionary accrual measures. We find that firms with steeper and more convex performance pricing schedule have significantly larger discretionary accruals, and results are robust with various measures of discretionary accruals used in the literature.

Since bank reputation and prior lending relationship could serve as an effective monitoring mechanism, which could potentially constraint managers' incentives for earnings management. We document evidence supporting this conjecture. We find that the relation between slope/convexity of performance pricing loans and discretionary accruals is positive and significant, but only in firms borrowing from banks with low reputation or banks with no prior lending relationship. In contrast, slope/convexity of performance pricing loans is not significantly related to discretionary accruals in firms borrowing from banks with high reputation or banks with prior lending relationship.

Our study contributes to the literature on debt contracting and earnings management. It is the first study that directly examines the effect of performance pricing schedule on earning management. We also shed light on how banks assert their monitoring effects to mitigate borrowers' incentive to manipulate accounting information in the context of performance pricing loans.

The rest of paper proceeds as following. Section 2 provides a literature review and develops hypotheses. Section 3 describes our sample, summary statistics and different variables. Section 4 reports empirical results and section 5 concludes the paper.

2. Literature Review and Hypotheses Development

2.1. Earning Management and Debt Contracting

Under generally accepted accounting principles, managers have discretion in reporting earnings. There are several ways to manage reported earnings, such as changing inventory accounting methods and accelerating recognition of revenue. Managers have incentives to manipulate earnings because of corporate events such as stock offers and acquisitions, because CEOs have large option portfolios, or because they have some important thresholds to meet (Teoh, Welch and Wong, 1986; Burns and Kedia, 2006; DeFond and Jiambalvo, 1994; Daniel, Denis and Naveen, 2008).

Many studies have examined whether managers are opportunistic in terms of managing earnings. Those literatures examine earning management around corporate events, managerial incentives for earning management and whether firms manage earnings to meet important thresholds (Daniel, Denis and Naveen, 2008). Existing research of earning management associated with loan contracts generally focus on debt covenants. For example, positive accounting theory (Watts and Zimmerman, 1986, 1990) suggests that managers have the incentive to change accounting method or make financial reporting decisions that reduce the likelihood of violating accounting-based covenants in debt contracts. Other studies examine the manager’s choices when firms are close to violating covenant constraints. DeFond and Jiambalvo (1994) find that abnormal accruals are positive and significant in the year prior to debt covenant violation. This demonstrates that managers use abnormal accruals to avoid debt covenant violation, and this also suggests that debt agreements motivate managers to manipulate income. Jaggi and Lee (2002) also show that managers of financial distressed firms use income-increasing discretionary accruals if they are able to obtain waivers for debt covenant violations, and use income-decreasing discretionary accruals if debt restructuring takes place or debts are renegotiated because waivers are denied. Sweeney (1994) examines the association between debt covenant violations and adopt of income-increasing accounting changes. She finds that managers make income-increasing accounting changes during periods prior to technical default. Daniel, Denis and Naveen (2008) find firms manage earnings upward at the time of cash shortfall because debt covenants prohibit firms from paying dividend as earning is below certain threshold.

Existing research of earning management has been focus exclusively on debt covenants, and research of earning management associated with performance pricing is limited. One related paper is provided by Beatty and Weber (2003). They find that borrowers that voluntarily change their accounting methods are more likely to make income-increasing accounting changes if their debt contracts include accounting-based performance pricing. My Chapter 1 (2010) is the first study examining the relationship between financial reporting quality and use of performance pricing provision. I document that the potential of firm to manipulate earning is one concern when banks issue performance pricing loans to borrowing firm. I find that firms with poorer accounting quality are less likely to receive performance pricing loans. Using financial restatement as a proxy for financial reporting quality, I document that the likelihood of receiving performance pricing loans is significantly reduced after borrowers' accounting quality deteriorates, e.g., after they restate their financial reports.

Improvement in a borrower's performance may result in a lower interest rate if the borrower reaches a better performance pricing level and deterioration in a borrower's performance may result in a higher interest rate if the borrower reaches a worse performance pricing level, performance pricing therefore provide managers additional incentives to make income-increasing accounting methods changes (Betty and Weber, 2003). Their results suggest that the incentive to lower interest rates through performance pricing influence borrowers' accounting method choices. Do firms manage accounting information to obtain a lower loan spread after they receive performance pricing loans?

This is the research question of this paper. We do not find any paper directly examine this question. Compared to covenants under which managing accounting information provide benefits to the borrower when the firm is close to violating covenant constraints, performance pricing provide a more continuous and direct link between accounting information and interest rates. Therefore, we expect that firms are more likely to manage earnings after they receive performance pricing loans with a steeper and more convex performance pricing schedule. Since steep and convex pricing schedule imply rapid decrease of interest payments when a firm improves its performance and rapid increase of interest payments when firm's performance deteriorates, the structure of performance pricing schedule will have an effect on firm's earning management. This leads us to the first hypothesis:

$H_{3.1}$: Steeper and more convex performance pricing schedules are associated with higher level of discretionary accruals.

2.2. Banks' Monitoring Role: Bank Reputation and Lending Relationship

A syndicated loan involves more than one lenders, who fall into one of two groups, namely, lead arrangers and participant lenders. Lead arrangers establish and maintain a relationship with the borrower, and take on the primary responsibility of information collection and monitoring. In contrast, participant lenders rarely directly negotiate with the borrowing firm. Lead arrangers are compensated with a fee for arranging and managing the syndicated loan, in addition to interest and commitment fee income. Since lead arrangers' monitoring and due diligence effort is unobservable, in order to ensure due diligence, lead arrangers are forced to retain a larger share of the loan when the borrower requires more intense due diligence and monitoring effort (Holmstrom, 1979; Sufi, 2007). Lead arrangers are ‘informed lenders’ and would monitor borrowers due to their large holding in bank loans, as well as their long-run reputation consideration. A more reputable bank with greater experience in the lending market would have a stronger incentive and better skills to monitor borrowers effectively. Billett, Flannery and Garfinkel (1995) find that stock market reaction to bank loan announcements is more positive as the lenders of bank loans have a higher credit rating. Pichler and Wilhelm (2001) argue that lead arrangers’ reputation could serve as an effective monitoring mechanism. We expect that bank monitoring is essential to mitigate the moral hazard problem of borrowers in managing earnings.

$H_{3.2}$: Given all else equal, borrowing from high reputation lead banks will mitigate the effect of performance pricing schedule on discretionary accruals.

In addition to lender reputation, prior lending relationship could mitigate information asymmetry between borrowers and lenders and reduce monitoring costs. Due to market friction, e.g., information asymmetry, lenders are unable to distinguish firms without devoting significant resources to evaluate the firm. Relationship banking has been viewed as a way to partly overcome those capital market frictions. Existing literature (see, for example, Diamond, 1991; Petersen and Rajan,1994) argues that bank monitoring plays an important role. Though close and repeated interaction, relationship lending allows a bank to acquire information through screening and monitoring from the borrower at a lower cost. Therefore, banks having repeated relationship with the borrowers would be able to monitor the firm’s conditions more effectively. Haubrich (1989) argue that in a repeated relationship between the bank and borrower, the bank can keep track of reports from the borrower and penalize the borrower if too many reports are bad. Firms can manage earnings when there is significant information asymmetry between borrowers and lenders, for example, when the firm borrows from a new lender. Therefore, we expect that firms borrowing from banks with prior lending relationship have less chance to manage earnings even if such kind of management are associated with great benefit, i.e., much lower cost of debt. On the other hand, because of the cost of monitoring and information production, firms borrowing from a new lender have more incentive to manage earnings especially when their performance pricing schedule indicates steep slope and high degree of convexity. Based on above analysis, we propose the following hypothesis:

$H_{3.3}$: Given all else equal, a prior lending relationship will mitigate the effect of performance pricing schedule on discretionary accruals.

3. Data and Summary Statistics

3.1. Data Source

Our study is based on bank loan data and firm's accounting information. Our bank loan data are obtained from the Dealscan database offered by Loan Pricing Corporation (LPC). The Dealscan database contains detailed information on bank loans (including term loans and lines of credit) worldwide, such as borrower and lender identity, loan amount, LIBOR spread, issuing and maturity date, financial and general covenants, etc.[25] LPC reports loan data at the 'deal' level as well as 'facility level'. The basic unit of observation in Dealscan is a 'facility' or 'tranche'. Several facilities are often grouped

[25] About 60% of Dealscan data are collected from SEC filings, and the rest are obtained from direct contact with borrowers and lenders. According to Carey and Hrycay (1999), the Dealscan database covers between 50% and 75% commercial loans in the U.S. by 1992, and by 1995 it covers a greater fraction.

into a deal. The facilities within a deal may differ in loan amounts, maturities, and other terms. Performance measures changes in different facilities. There are more than eight performance measures, such as Debt-to-EBITDA ratio, senior debt rating and leverage. Based on a sample from 1990-2007, Chapter 1 (2010) find that the most commonly used measure is debt-to-EBITDA ratio, which accounts for about half of the performance pricing loans. The second widely used performance measure is Senior Debt Rating, which accounts for about 22.3% of the performance pricing loans. All the other performance measures account for a small portion of the sample. Therefore, our study focuses on Debt-to-EBITDA based and Senior Debt Rating based performance pricing loans.

Accounting data of borrower are obtained from the Compustat database, which is firm-year level obs. Performance pricing schedule measures (slope and convexity) are obtained at facility level. To examine the relation between slope/convexity of performance pricing contracts and firm's accrual measures, we calculate dollar weighted average slope/convexity at firm-year level using ranks.

3.2. Slope and Convexity

Slope and convexity of the performance pricing schedule are used to measure the riskiness of a performance pricing loan. Steep slope and high degree of convexity imply rapid decrease of interest payments when a firm improves its performance and rapid increase of interest payments when firm's performance deteriorates. We construct average slope of Senior Debt Rating based performance pricing loans following Tchistyi, Yermack and Yun (2007). For each performance pricing loan contract, we find interest rate change of each credit rating increment. Then, each incremental change is divided by the difference of market yields of bonds over the same rating increments. After calculating market-adjusted slopes for each rating increment of a loan contract individually, we take their mean as the average slope for each contract. Under this scaling, non-performance pricing loans will have an average slope of zero. Average slope will be equal to/larger than/less than 1 if interest rate change of performance pricing loan is similar to/larger than/less than the change of prevailing market yields. Local slope calculation of Senior Debt Rating based performance pricing loans is also based on Tchistyi, Yermack and Yun (2007). We first find the rating increments immediately above and immediately below the company's rating at the time of loan issuance. Local slope is calculated as the average over those rating incremental change.

$$\text{Local slope}=0.5\left\{\frac{Spread(i-1)-Spread(i)}{MarketSpread(i-1)-MarketSpread(i)}+\frac{Spread(i)-Spread(i+1)}{MarketSpread(i)-MarketSpread(i+1)}\right\}$$

Where *Spread(i)* is the firm's interest cost above LIBOR at rating *i*, and *i* is firm's rating at time of loan issuance. *MarketSpread(i)* is market yields above LIBOR of bonds at rating *i*.

Convexity provides an alternative measure of performance pricing contract riskiness. Convex performance pricing schedule accelerates the rate of interest payment increase and therefore accelerates the rate of financial burden when firm's performance deteriorates. We construct convexity of Senior Debt Rating based performance pricing loans following Tchistyi, Yermack and Yun (2007). For a particular Senior Debt Rating based performance pricing schedule, CR_l and CR_h denote the lowest and highest credit ratings and *N(CR)* denotes the number of rating notches between *CR* and CR_h. Linear extrapolation of performance pricing schedule r is calculated as follows:

$$r_l(CR) = r(CR_h) + \frac{r(CR_l) - r(CR_h)}{N(CR_l)} N(CR)$$

Then, convexity of the performance pricing schedule is defined as the greatest deviation from the linear extrapolation.

$$x_r = \frac{\mathrm{sign}\ (\mathrm{r_L(CR)} - \mathrm{r(CR)}) * \max_{\mathrm{CR} \in [\mathrm{CR_h}, \mathrm{CR_l}]} |\mathrm{r_L(CR)} - \mathrm{r(CR)}|}{r(CR_l) - r(CR_h)}$$

Where sign(a) is equal to 1 if a≥0 and equal to -1 if a<0.

For the Debt-to-EBITDA based performance pricing loans, we construct slope and convexity based on above method. For each performance pricing loan contract, we find interest rate change of each debt-to-EBITDA increment. Then, each incremental interest rate change is divided by the difference of debt-to-EBITDA ratio over the same increment. After calculating slopes for each debt-to-EBITDA increment of a loan individually, we take their mean as the average slope for each contract. Under this scaling, larger average slope indicates larger interest rates change of performance pricing loan over unit of debt-to-EBITDA ratio change. To calculate local slope of Debt-to-EBITDA based performance pricing loans, we first find the debt-to-EBITDA increments immediately above and immediately below the company's debt-to-EBITDA ratio at the time of loan issuance. Local slope is calculated as the average over those incremental changes.

Local slope=

$$0.5\left\{\frac{Spread(i-1) - Spread(i)}{Debt-to-EBITDA(i-1) - Debt-to-EBITDA(i)} + \frac{Spread(i) - Spread(i+1)}{Debt-to-EBITDA(i) - Debt-to-EBITDA(i+1)}\right\}$$

Where *Spread(i)* is the firm's interest cost above LIBOR at debt-to-EBITDA ratio *i*, and *i* is firm's debt-to-EBITDA ratio at time of loan issuance. *Debt-to-EBITDA (i)* is the debt-to-EBITDA ratio *i*.

For a particular Debt-to-EBITDA based performance pricing schedule, DCF_l and

DCF_h denote the lowest and highest debt-to-EBITDA ratio and *N(DCF)* denotes the difference between *DCF* and DCF_l. Linear extrapolation of performance pricing schedule r is calculated as follows:

$$r_L(DCF) = r(DCF_l) + \frac{r(DCF_h) - r(DCF_l)}{N(DCF_h)} N(DCF)$$

Then, convexity of the performance pricing schedule is defined as the greatest deviation from the linear extrapolation.

$$x_r = \frac{\text{sign}\ (\mathrm{r_L}(DCF) - \mathrm{r}(DCF)) * \max_{DCF\epsilon[DCF_\mathrm{l},DCF_\mathrm{h}]} |\mathrm{r_L}(DCF) - \mathrm{r}(DCF)|}{r(DCF_h) - r(DCF_l)}$$

Where sign(a) is equal to 1 if a≥0 and equal to -1 if a<0.

To examine the relation between slope/convexity of performance pricing contracts and firm's accrual measures, we need to calculate slope/convexity at firm-year level. We use 'rank' to obtain firm-year level slopes of a sample including Debt-to-EBITDA based performance pricing loans, Senior Debt Rating based performance pricing loans and non-performance pricing loans. Average slopes of Debt-to-EBITDA based performance pricing loans are ranked into quarters, with the largest 25% average slopes taking a value of 4 and the least 10% taking a value of 1. Average slopes of Senior Debt Rating based performance pricing samples are ranked in the same way, and non-performance pricing loans taking a rank of zero. Average slopes of whole sample is the facility amount weighted average of those ranks. We aggregate dollar weighted average slope/convexity at firm-year level in following way. For a particular firm, we first find its outstanding facilities in each year. Slope/convexity in a particular year is weighted average ranks of slope/convexity of all outstanding facilities of a firm in a year, with the weight=facility amount/total outstanding facility amount of the firm in that year. Therefore, firm-year average slope/convexity is calculated as follows:

$$\text{Firm} - \text{year slope/convexity} =$$

$$\frac{\text{sum of (outstanding facility amount}*\text{its rank of slope/convexity)}}{\text{total outstanding facility amount}}$$

For those facilities with missing maturity, we set facility maturity date =facility start date +median of maturity in years of our sample*365.

3.3. Firm Characteristic Variables

To examine our hypotheses above on the effect of performance pricing schedule on manager's earning manipulation, we construct the following variables. Detailed variable definitions are provided in Appendix C.

3.3.1. Accrual Measures

To measure earning manipulation, we construct accrual measures following Daniel, Denis and Naveen (2008). Total accrual is defined as income before extraordinary items (EBEXTRA) minus operating cash flows. There are two components of total accruals: non-discretionary and discretionary accruals. Managers have discretion over the discretionary accruals, not over the non-discretionary accruals.

Non-discretionary and discretionary accruals are estimated following the cross-sectional model of Jones (1991). We first regress following model:

$$\frac{total\ accruals_{j,t}}{assets_{j,t-1}} = c + \varphi_1 \frac{\Delta Sales_{j,t}}{assets_{j,t-1}} + \varphi_2 \frac{PPE_{j,t}}{assets_{j,t-1}}$$

Total accruals = income before extraordinary items (EBEXTRA) – operating cash flows

Here, each regression is estimated separately for each two-digit SIC industry for each year, using all firms in Compustat. Residual and predicted values from above regressions are the discretionary and non-discretionary components of total accruals. The discretionary and non-discretionary components are multiplied by firm's lagged assets to get the dollar value of discretionary and non-discretionary accruals. The dollar values of discretionary accruals are accrual measure we used in our analysis. Besides discretionary accrual measure 'Modified Jones (1991)' mentioned above, we use other four discretionary accrual measures. 'Modified KLW (2005)' is based on Modified Kothari, Leon, Wasley (KLW) model. We first calculate asset-scaled discretionary accruals for each firm based on Jones (1991), in which ROA is included as an additional regressor. Then we compute the discretionary accruals of a firm matched based on ROA, industry and year. The difference between these two discretionary accruals is our discretionary accrual measure 'Modified KLW (2005). 'TWW (1998)' is based on Teoh, Welch, and Wong (1998) model. In their method, total accruals are based on net income, instead of EBEXTRA, i.e. total accruals = net income – operating cash flows. 'BS (2006)' is based on Ball and Shivakumar (2006) model. Ball and Shivakumar (2006) show that accrued loss recognition is more prevalent than accrued gain recognition. Therefore, we include variables that capture the asymmetric timely loss recognition of firms in this method 'Modified DD (2002)' is based on Dechow and Dichev (2002) model. We augment the Dechow and Dichev (2002) model with variables from Jones (1991) model.

3.3.2. Other Firm Characteristic Control Variables

In addition to the variables discussed above, we also control for other firm characteristics (firm size, market-to-book ratio, leverage and retained earnings) that might affect the level of discretionary accruals. We measure firm size using the natural logarithm of total assets. The effect of firm size on the discretionary accruals is not clear. On one side, larger firms are in general more transparent because of more analyst coverage. Therefore, larger firms seem to be less likely to manipulate earnings. On the other hand, Kim, Liu and Rhee (2003) find that both large and small firms manage earnings aggressively. While small firms are more likely to manage earnings to avoid reporting losses, large- and medium-sized firms exhibit more aggressive earning management to avoid reporting earning decreases. *Market-to-book ratio* is is defined as the ratio of market value of assets (book value of debt plus market value of equity) and book value of total assets. Leverage is defined as the ratio of total amount of debt and book value of assets. Retained earning is from Balance-sheet and it is used to control for the potential inventory of payable funds. The effect of retained earnings on discretionary total accruals is also not clear. Daniel, Denis and Naveen (2008) find retained earnings have a positive effect on discretionary accruals in some regression and negative effect in others.

3.4. Measures of Bank Reputation and Lending Relation

Our analysis on bank reputation and prior lending relation focuses on lead arrangers.[26] Following Sufi (2007), we classify lenders listed in “Lender-Lead Arranger” as lead arranger if this variable is available from the custom report of Dealscan. Otherwise, we classify lenders having a “lead role” listed in “Lenders-All lenders” as the lead arranger. To make data collection manageable, we focus on the top 100 lead

[26] While most of loans in Dealscan involve several lenders, it is the lead arrangers’ responsibility to negotiate directly with the borrower for all contract terms. Participant lenders rarely directly negotiate with the borrowing firm and usually hold a relatively small share of the loan.

arrangers in Sufi (2007). This selection will not result in any bias, because according to Sufi (2007), the top 100 lenders represent about 96% of the total number of loans. To take into account bank mergers during our sample period, we track all mergers and acquisitions of financial institutions, and allow the acquiring banks to inherit all the lending history of the acquired bank after the acquisition date. For example, in April 1998, First Union Corp. acquired CoreStates Financial Corp. with a name of merged entity 'First Union Corp.' Thus after April 1998, First Union Corp. inherited CoreStates' entire lending history as we compute lender market share and lead bank-borrower relation.

Following previous literature (e.g., Bharath, Dahiya, Saunders, and Srinivasan, 2007), we use a lead arranger's market share in lending in the previous five years as a proxy for lead arranger's reputation. It is computed as the dollar amount of loans arranged by a particular lead bank during the previous 5 years divided by the total amount of loans issued in the market in the same period. We use a dummy variable '*existence of prior lending relation*' to measure whether the firm has a prior lending relationship with the lending banks. It is equal to one if the lead bank of the current loan has acted as a lead bank for a loan from the same firm during the prior 5 years, and zero otherwise.

4. Empirical Results

4.1. Summary Statistics

We present summary statistics of our sample in Table 3.1. Our sample consists of a total of 4,279 companies from 1993 to 2007. As shown in the table, the median discretionary accruals are close to zero, this is because discretionary accruals are the residuals from a regression of total accruals on firm characteristics. My Chapter 1 (2010) documents that about 62.5% loans are non-performance pricing loans. Average slope, local slope and convexity of non-performance pricing loans take a value of zero. Thus, not surprisingly, the medians of average slope, local slope and convexity are close to zero. The average firm in our sample has over $2.5 billion in total assets, and has retained earnings of $495 million.

4.2. Effect of Performance Pricing Schedule on Discretionary Accruals

As mentioned earlier, we use slope and convexity of the performance pricing schedule to measure the riskiness of a performance pricing loan. High degrees of slope and convexity accelerate the rate of interest payment decrease when a firm improves its performance and accelerate the rate of interest payment increase and thereby the rate of financial burden when firm's performance deteriorates. Therefore, high degrees of slopes and convexities provide incentive to managers to manage earnings upwards.

To examine the effect of performance pricing loans on firm's earning management, we estimate following models:

$$Discretionary\ accruals_t = \alpha_1 + \beta_1 Slope / Convexity + \sum_i \gamma_i Control\ variables_{t\text{-}1} + \varepsilon_t .$$

(3.1)

Here, we use five different discretionary accrual measures as described earlier. Control variables include firm characteristic variables mentioned earlier, two-digit SIC dummies and year dummies. The variable of our interest is *Slope/Convexity*, which captures the riskiness of performance pricing loans. Table 3.2 presents the OLS regression results of above model. Panel A reports results of multiple regressions that examine the effect of average slope of performance pricing schedule on different discretionary accruals. In model (1), the coefficient estimate of *Average slope* is positive and statistically significant at 1% level. It suggests that firms with a greater average slope in their performance pricing loans have significantly larger discretionary accruals. When we use different accrual measures in model (2) – (5), we get similar results. The coefficient estimates of average slope are generally positive and statistically significant, except model (5) using discretionary accrual measure ‘Modified DD (2002)’ as dependent variable. Those results are consistent with our hypothesis that firms with steeper pricing schedule provide more incentive to managers to manipulate earnings. We also find that firm size and firm’s retained earnings have significant effect on discretionary accruals, although they have a positive effect on discretionary accruals in some regression and negative effect in others. Those results are consistent with Kim, Liu and Rhee (2003) and Daniel, Denis and Naveen (2008).

Panel B presents the results of regressions examining the effect of local slope of performance pricing schedule on different discretionary accruals. The coefficient estimates of *Local slope* are generally positive and statistically significant in two models, suggesting that firms with greater local slopes of performance pricing loans have larger discretionary accruals. Those results support our hypothesis, although they are not as strong as the results from Panel A. In Panel C, we examine the effect of convexity of performance pricing schedule on different discretionary accruals. The results indicate that the coefficient estimates of *Convexity* are significantly positive in all five models, which implies that firms with loans of high degree of convexity have large discretionary accruals. This further provides evidence that the performance pricing schedule has an effect on manager's incentive to manage earnings upwards.

In general, the findings in Table 3.2 support the view that performance pricing schedule has an effect on earning management. Greater slope and convexity of performance pricing schedule provide firms more incentive to manage earnings upwards.

4.3. Bank Reputation, Performance Pricing Schedule, and Discretionary Accruals

We document a positive relationship between steep and convex performance pricing schedule and earning management. Next we will examine whether bank reputation would mitigate managers' incentive to manipulate earnings, as suggested in our hypothesis H_2. For that purpose, we include a *High bank reputation dummy* and its interaction with *Average slope* in the regression models as shown below:

$$\begin{aligned} \textit{Discretionary Accruals}_t &= \alpha_1 + \beta_1 \textit{High bank reputation dummy} + \beta_2 \textit{Average slope} \\ &+ \beta_3 \textit{Average slope} \times \textit{High bank reputation dummy} + \sum_i \gamma_i \textit{Control variables}_{t\text{-}1} + \varepsilon_t, \end{aligned} \tag{3.2}$$

We also replace *Average slope* with *Local slope* or *Convexity* to capture the performance pricing schedule. In equation (3.2), β_2 captures the effect of performance pricing schedule on discretionary accruals for lead banks with low reputation. The impact of performance pricing schedule on discretionary accruals for lead banks with high reputation is captured by $\beta_2 + \beta_3$ in equation (3.2), while β_3 measures the differential effect of performance pricing schedule on discretionary accruals between high versus low bank reputation.

Table 3.3 reports the OLS regression results from above model. Panel A presents results examining the effect of average slope of performance pricing schedule on discretionary accruals conditional on bank reputation. In model (1), the coefficient estimate of *Average slope* is positive and significant, suggesting that as firms borrow from low reputation lead banks, discretionary accruals rise significantly if the firm has greater average slope of performance pricing schedule. However the coefficient estimate of *Average slope**High bank reputation dummy* is negative and significant, which leads to an insignificant coefficient estimate of $\beta_2 + \beta_3$. $\beta_2 + \beta_3$ captures the impact of average slope on discretionary accruals for banks with high reputation. Therefore, this result indicates that as the firm borrows from high reputation banks, discretionary accruals do not increase significantly even if the firm has a greater average slope of performance pricing schedule. Although not all of the coefficient estimates of β_3 are significant if we use different discretionary accrual measures, we can still find the trend that there is no significant relationship between steep performance pricing schedule and earning management if firms borrow from banks with high reputation.

Panel B and C present results examining the effect of local slope / convexity of performance pricing schedule on discretionary accruals conditional on bank reputation. The coefficient estimates of *Local slope* are positive and significant and coefficient estimates of $\beta_2 + \beta_3$ are negative and significant in four regressions out of five. Those results strongly support that as firms borrow from low reputation banks, discretionary accruals rise significantly if the firm has a steep local slope of performance pricing schedule. The regression results of Panel C also provide evidence that as firms borrow from high reputation banks, discretionary accruals do not increase significantly even if firms have a high degree of convexity of performance pricing schedule.

Collectively, we find evidence supporting hypothesis $H_{3.2}$ that as firms borrow from high reputation lead banks, discretionary accruals do not rise significantly even if firms have a steep and convex performance pricing schedule. If firms with a steep and convex performance pricing schedule borrow from low reputation lead banks, discretionary accruals increase significantly. Those results also support the view that banks with high reputation are more likely to monitor firms efficiently and they mitigate borrowers' incentive to manage earnings.

4.4. Prior Lending Relationship, Performance Pricing Schedule, and Discretionary Accruals

We find some evidence that banks with high reputation can mitigate borrowers' incentive to manipulate earnings. Next we will examine whether prior lending relation would mitigate the effect of performance pricing schedule on earning management, as suggested in our hypothesis H_3. We use the similar model:

$$\begin{aligned} Discretionary\ Accruals_t &= \alpha_1 + \beta_1 Existence\ of\ \ prior\ \ prior\ lending\ relation \\ &+ \beta_2 Average\ \ slope + \beta_3 Average\ \ slope \times Existence\ of\ \ prior\ lending\ relation \\ &+ \sum_i \gamma_i Control\ variables_{t\text{-}1} + \varepsilon_t, \end{aligned} \tag{3.3}$$

We also replace *Average slope* with *Local slope* or *Convexity* to capture the performance pricing schedule. In equation (3.3), β_2 captures the effect of performance pricing schedule on discretionary accruals for banks without any prior lending relationship, and β_3 measures the differential effect of performance pricing schedule on discretionary accruals between prior versus no prior lending relation.

Table 3.4 presents the OLS regression results of equation (3.3). Panel A, Panel B and Panel C report results examining the effect of average slope, local slope and convexity of performance pricing schedule on discretionary accruals conditional on prior lending relationship, respectively. In model (1) of Panel A, the coefficient estimate of *Average slope* is positive and significant, suggesting that as firms borrow from new banks, discretionary accruals increase significantly if the firm has steep performance pricing schedule. The coefficient estimate of *Average slope* Existence of Prior lending relation* is negative and significant, which indicates significant differential effect of average slope on discretionary accruals between prior and no prior lending relationship. As firms borrow from banks with prior lending relationship, discretionary accruals do not increase significantly even if the firm has steep performance pricing schedule. The coefficient estimates of β_3 are not always statistically significant as we use different discretionary accrual measures. However, this still provide evidence of the differential effect of performance pricing schedule on discretionary accruals between prior versus no prior lending relation.

Panel B and C present results examining the effect of *local slope / convexity* of performance pricing schedule on discretionary accruals conditional on prior lending relationship. Those results provide evidence that as firms borrow from banks with prior lending relationship, discretionary accruals will not increase significantly even if those firms have a high degree of local slope and convexity of performance pricing schedule.

In summary, we find evidence supporting hypothesis $H_{3.3}$ that prior lending relationship mitigate the effect of performance pricing schedule on firm's earning management. The positive association between the slope or convexity of performance pricing loans and discretionary accruals is significantly reduced as the lenders have had aprior lending relationship with the borrowers. Those results also provide evidence of banks' monitoring role.

5. Conclusion

In this study, we examine how a firm's performance pricing loans affect manager's incentive to manipulate earning. We find that firms with a greater slope or convexity in their performance pricing loans have significantly larger discretionary accruals, suggesting steep and convex performance pricing schedule has an effect on firm's earning management.

In addition to lender reputation, prior lending relationship could mitigate information asymmetry between borrowers and lenders and reduce monitoring costs. We further investigate whether high lenders' reputation and prior lending relation mitigate firm's incentive to manage earnings associated with steep and convex performance pricing schedule. We find that as firms borrow from banks with high reputation or from banks with prior lending relationship, discretionary accruals do not rise significantly even if firms have a steep and convex performance pricing schedule. However, discretionary accruals rise significantly if firms with steep and convex performance pricing schedules borrow from banks with low reputation or from banks without any prior lending relationship. These results suggest that bank reputation and prior lending relation serve as an effective monitoring mechanism, which in turn mitigates managers' incentive to manager earnings.

Compared with previous research on performance pricing loans, we directly examine the earning management associated with performance pricing schedule and the role of high bank reputation and prior lending relationship on earning management. Our further research on this issue would be whether and how firms manage earnings when their performance measure is close to some increments. This kind of study would provide us more information of firm's behavior when their performance is close to some key points.

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Appendix A: Variable Definitions of Chapter 1

Variable	Definition
Performance Pricing Type	
Debt to EBITDA	Outstanding debt divided by (net income plus depreciation and other non-cash charges).
Senior Rating	Rating of outstanding debt on a senior basis.
Leverage ratio	Debt divided by capitalization (or equity).
Senior Debt to EBITDA	Outstanding debt on a senior basis divided by (net income plus depreciation and other non-cash charges).
Fixed Charge Coverage	Equal to EBITDA divided by (interest charges paid plus long-term lease payments).
Debt to Tangible Net Worth	Total debt divided by (net worth minus intangible assets).
Interest Coverage	Equal to EBITDA divided by interest expense.
Debt Service Coverage	Equal to EBITDA divided by (interest expense plus the quantity of principal repayments).
Loan Characteristics	
Ln(loan size)	Natural logarithm of loan amount in US dollars.
Maturity	Time to maturity of the loan in years
Revolver	Dummy=1 if the loan is a revolver (364-Day Loan, Revolver/Line < 1 Yr., Revolver/Line >= 1 Yr., Revolver/Term Loan)
Secured	Dummy=1 if the loan is secured
Senior	Dummy=1 if the loan is senior
Covenant	Dummy=1 if the loan has any financial covenant or general covenant
Syndicate	Dummy=1 if the loan is syndicated
Borrower Characteristics	
Firmsize	Natural logarithm of book value of assets
Market-to-book	The sum of market value of equity and book value debt divided by book value of total assets
ROA	Net income divided by total assets
Credit rating	A credit rating score based on Standard & Poor's Senior Debt Rating from Dealscan. AAA rating is assigned a score of 22, AA^+ rating is assigned a score of 21, …, and D rating is 1. We assign a score of 0 when rating is unavailable.
Retstd	Stock return volatility that is calculated as the standard deviation of 12 monthly returns in previous year.
CFstd	Cash flow volatility that is computed as the standard deviation of net cash flow over the past 16 quarters divided by the average book assets over the same

	period.
Zscore	Altman (1968) Z-score that is computed as 1.2*data179/data6 + 1.4*data36/data6 + 3.3*data178/data6 + 0.6*(data199*data25/data181) + data12/data6.
Oscore	Ohlson (1980) O-score that is computed as -1.32-0.407*log(data6) + 6.03*data181 - 1.43*(data179/data6) + 0.076*(data5/data4) - 1.72*(1 if data181>data6, 0 otherwise) - 0.521*(data172-lag(data172) /{|data172$_t$|+|lag(data172)|.
Default Index	A rank score based on five measures of default risk: credit rating, Retstd, CFstd, Zscore and Oscore. Higher value of default index denote higher default risk.
Rating dummy	A dummy variable that equals one if any type of S&P debt rating of a firm is available in Compustat.
Tangibility	Net PP&E divided by total assets.
Lender Characteristics	
Strength of lead bank-borrower prior lending relation ($)	It is computed as the dollar amount of loans arranged by a particular lead bank and its predecessors for a firm during the previous 5 years divided by the total dollar amount of loans borrowed by the firm during the same period.
Strength of lead bank-borrower prior lending relation (N)	It is computed as the number of loans arranged by a particular lead bank and its predecessors for a firm during the previous 5 years divided by the total number of loans borrowed by the firm during the same period.
Accounting Quality	
DD_AQ10	The standard deviation of residuals of following equation over the years *t*-9 through *t:* $CA_{j,t}=c+\varphi_1 CFO_{j,t-1}+ \varphi_2 CFO_{j,t}+\varphi_3 CFO_{j,t+1}+ \upsilon_{j,t}$. All variables are scaled by assets of that year. Estimation of Dechow and Dichev (2002, hereafter DD) model involves two steps. First, we estimate above equation annually for each firm for each of the ten years *t*-9 through *t*. Then we calculate the standard deviation of firm *j*'s residuals across the ten years, i.e., $\upsilon_{j,t}$ through $\upsilon_{j,t-9}$.
DD_AQ5	The same as DD_AQ10 except that it is the standard deviation of residuals over the five years *t*-4 through *t*.
MDD_AQ10	Following McNichols (2002), we estimate the modified DD model (hereafter MDD) as follows:

	$CA_{j,t}=c+\varphi_1 CFO_{j,t-1}+\varphi_2 CFO_{j,t}+\varphi_3 CFO_{j,t+1}+\varphi_4 \Delta Sales_{j,t} + \varphi_5 PPE_{j,t} +\upsilon_{j,t}$. MDD model is equivalent to the DD model except that changes in sales and PPE are added. All variables are scaled by assets of that year. MDD_AQ10 is the standard deviation of residuals of the above equation over the years *t*-9 through *t*. MDD model involves two steps. First, we estimate above equation annually for each of the Fama and French (1997) 48 industry groups having at least 20 firms for each of the ten years *t*-9 through *t*. Then we calculate the standard deviation of firm *j*'s residuals across the ten years, i.e., $\upsilon_{j,t}$ through $\upsilon_{j,t-9}$.
MDD_AQ5	The same as MDD_AQ10 except that it is the standard deviation of residuals over the five years *t*-4 through *t*.
ADD_AQ10	It is the average of the absolute value of $\upsilon_{j,t}$ through $\upsilon_{j,t-9}$ of DD model.
ADD_AQ5	It is the average of the absolute value of $\upsilon_{j,t}$ through $\upsilon_{j,t-4}$ of DD model.
AMDD_AQ10	It is the average of the absolute value of $\upsilon_{j,t}$ through $\upsilon_{j,t-9}$ of MDD model.
AMDD_AQ5	It is the average of the absolute value of $\upsilon_{j,t}$ through $\upsilon_{j,t-4}$ of MDD model.

Appendix B: Variable Definitions of Chapter 2

Variable	Definition
Loan Characteristics	
Loan spread	Spread over LIBOR rate in basis points
Log(loan size)	Natural logarithm of loan amount in US dollars
Log(loan maturity)	Natural logarithm of time to maturity of a loan in months
Secured	A dummy variable taking a value of 1 if the loan is secured, and 0 otherwise.
Performance pricing	A dummy variable taking a value of 1 if a performance pricing provision is included in a loan contract, and 0 otherwise.
Upfront fee (basis points)	A fee paid by the borrower upon closing of a loan
Annual fee (basis points)	Annual charge against the entire loan amount
Loan purpose dummies	Five dummies for various loan purposes, including corporate purposes, debt repayment, working capital, takeover, and all other purposes
Borrower Characteristics	
Log(assets)	Natural logarithm of book value of assets
Market-to-book	The sum of market value of equity and book value of debt divided by book value of total assets
Leverage	Total debt divided by total assets
ROA	Net income divided by total assets
Tangibility	Net PP&E divided by total assets
Cash flow volatility	Cash flow volatility that is computed as the standard deviation of net cash flow over the past 16 quarters divided by the average book assets over the same period
Zscore	Altman (1968) Z-score that is computed based on Compustat data items according to the following formula: 1.2*data179/data6 + 1.4*data36/data6 + 3.3*data178/data6 + 0.6*(data199*data25/data181) + data12/data6
Cash flow	Net income divided by total assets
Cash holding	Cash and short-term investments divided by total assets
Large firm	A dummy variable taking a value of 1 if the firm's sales revenue are at least $1 billion, and 0 otherwise
Investment grade	A dummy variable taking a value of 1 if the firm has a rating of BBB− or higher, and 0 otherwise
Stock return volatility	The standard deviation of 12 monthly returns in previous year.
No public debt dummy	A dummy variable taking a value of 1 if a firm does

	not have any type of S&P debt rating available in the Compustat database, and 0 otherwise.
Lead bank market share (bank reputation)	Dollar amount of loans arranged by the lead bank in a previous 5 yearsas the fraction of the total amount of loans issued in the entire market in during the same period.
Lead bank-borrower lending relation	For a borrower j in a particular year, it is the amount of loans arranged by bank i and its predecessors during the previous 5 years divided by the total amount of loans borrowed by borrower j during the same period.

Macroeconomic factors

Credit spread	Yield difference between AAA rated corporate bond and BAA rated corporate bond
Term spread	Difference between 10-year Treasury yield and 2-year Treasury yield

Appendix C: Variable Definitions of Chapter 3

Variable	Definition
Discretionary accruals	
Modified Jones (1991)	We first regress following model: $\frac{total\ accruals_{j,t}}{assets_{j,t-1}} = c + \varphi_1 \frac{\Delta Sales_{j,t}}{assets_{j,t-1}} + \varphi_2 \frac{PPE_{j,t}}{assets_{j,t-1}}$ Total accruals = income before extraordinary items (EBEXTRA) – operating cash flows Here, each regression is estimated separately for each two-digit SIC industry for each year, using all firms in Compustat. Residuals from above regressions are the discretionary components of total accruals. The discretionary components are multiplied by firm's lagged assets to get the dollar value of discretionary accruals, which are discretionary accruals we used in our analysis.
Modified KLW (2005)	Based on Modified Kothari, Leon, Wasley (KLW) model. We first calculate asset-scaled discretionary accruals for each firm based on Jones (1991), in which ROA is included as an additional regressor. Then we compute the discretionary accruals of a firm matched based on ROA, industry and year. The difference between these two discretionary accruals is our discretionary accrual measure 'Modified KLW (2005).
TWW (1998)	Based on Teoh, Welch, and Wong (1998) model. In their method, total accruals = net income – operating cash flows.
BS (2006)	Based on Ball and Shivakumar (2006) model. This method includes variables that capture the asymmetric timely loss recognition of firms.
Modified DD (2002)	Based on Dechow and Dichev (2002) model. We augment the Dechow and Dichev (2002) model with variables from Jones (1991) model.

Borrower Characteristics

Retained earnings	Data36 from Compustat
Firmsize	Natural logarithm of book value of assets
Leverage	Total debt divided by total assets
Market-to-book	The sum of market value of equity and book value debt divided by book value of total assets

Lender Characteristics

High bank reputation dummy	A dummy variable taking a value of 1 if a lead arranger's market share in lending in the previous five years is above sample median, and 0 otherwise
Existence of prior lending relationship dummy	A dummy variable taking a value of 1 if the lead bank of the current loan has acted as a lead bank for a loan from the same firm during the prior 5 years, and 0 otherwise

Table 1.1: Summary Statistics of Our Sample

Our sample consists of 16,784 Dealscan loans issued by firms from 1990 to 2007 that have data available in Compustat and CRSP. Performance pricing (non-performance pricing) loans are those having (having no) performance pricing provision in loan contract. All variables are as defined in Appendix A.

Panel A: Percentage of performance pricing loans

Type	# of Loans	Fraction
Performance pricing loans	6,294	37.5%
Non-performance pricing loans	10,490	62.5%
Total	16,784	100%

Panel B: Sample distribution of performance measures used in the performance pricing provision

Type	# of Loans	Fraction
Debt to EBITDA	3,213	54.6%
Senior Rating	1,314	22.3%
Leverage	281	4.8%
Senior Debt to EBITDA	207	3.5%
Fixed Charge Coverage	146	2.5%
Debt to Tangible Net Worth	120	2.0%
Interest Coverage	77	1.3%
Debt Service Coverage	55	0.9%
Others	477	8.1%
Total	5,890	100%

* We exclude 404 performance priced loans that involve more than one performance measure in the loan contract, which yields 5,890 performance pricing loans.

Panel C: Univariate analysis of loans with and without performance pricing

	Mean Value			
Variable	Performance Pricing Loans	Non-Performance Pricing Loans	Difference	T-statistics
Loan Characteristics				
Loan size ($billion)	0.2560	0.1770	0.0790	12.21***
Maturity	4.1573	3.9035	0.2538	5.68***
Revolver	0.7609	0.5880	0.1729	23.14***
Secured	0.5848	0.4421	0.1427	18.07***
Senior	0.9805	0.9040	0.0765	19.35***
Covenant	0.9569	0.3984	0.5586	86.18***
Syndicate	0.8499	0.6014	0.2484	35.04***
Borrower Characteristics				
Assets ($billion)	1.6257	1.6305	-0.0048	-0.09
ROA	0.1449	0.1163	0.0286	19.46***
Market-to-book	1.7302	1.6346	0.0958	7.10***
Credit rating	6.0863	4.9241	1.1622	11.97***
Retstd	0.1239	0.1358	-0.0119	-11.30***
CFstd	0.0558	0.0598	-0.0040	-7.28***
Zscore	3.6701	3.3791	0.2910	6.78***
Oscore	0.0600	0.0627	-0.0027	-1.37
Default_index	0.5561	0.5843	-0.0283	-15.57***
Lender Characteristics				
Lead bank-borrower lending relation ($)	0.5002	0.4746	0.0256	3.72***
Lead bank-borrower lending relation (N)	0.4822	0.4560	0.0262	3.92***
Accounting Quality				
DD_AQ10	0.0202	0.0233	-0.0031	-6.07***
DD_AQ5	0.0092	0.0109	-0.0017	-5.86***
MDD_AQ10	0.0423	0.0482	-0.0059	-9.16***
MDD_AQ5	0.0393	0.0455	-0.0062	-9.42***
ADD_AQ10	0.0144	0.0166	-0.0022	-5.84***
ADD_AQ5	0.0065	0.0076	-0.0011	-5.27***
AMDD_AQ10	0.0373	0.0421	-0.0048	-9.04***
AMDD_AQ5	0.0368	0.0416	-0.0048	-8.70***

***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

Table 1.2: Accounting Quality and the Likelihood of Using Performance Pricing Loans

This table reports logistic regression results explaining the choice of using performance pricing provision. Dependent variable is a performance pricing dummy, which equals one if the loan spread is tied to a performance measure, and zero otherwise. All variables are as defined in Appendix A. Higher values of *Accrual Quality* variables (DD_AQ10, DD_AQ5, MDD_AQ10, MDD_AQ5, ADD_AQ10, ADD_AQ5, AMDD_AQ10, AMDD_AQ5) indicate poorer accounting quality. Standard errors are clustered at firm level. P-values are reported in parentheses below each coefficient estimate.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DD_AQ10	-3.208							
	(0.008)							
DD_AQ5		-4.569						
		(0.008)						
MDD_AQ10			-3.221					
			(0.001)					
MDD_AQ5				-2.793				
				(0.003)				
ADD_AQ10					-3.777			
					(0.016)			
ADD_AQ5						-5.129		
						(0.023)		
AMDD_AQ10							-3.159	
							(0.011)	
AMDD_AQ5								-1.985
								(0.080)
Firmsize	-0.157	-0.152	-0.177	-0.169	-0.150	-0.149	-0.170	-0.163
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	2.880	2.875	2.701	2.635	2.963	2.993	2.844	2.893
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market-to-book	-0.061	-0.065	-0.046	-0.049	-0.054	-0.058	-0.041	-0.051
	(0.138)	(0.111)	(0.273)	(0.241)	(0.153)	(0.130)	(0.288)	(0.193)
Ln(loan size)	0.344	0.346	0.352	0.353	0.341	0.343	0.352	0.352
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity	0.108	0.106	0.105	0.104	0.098	0.098	0.095	0.095
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Revolver	1.114	1.110	1.112	1.105	1.091	1.091	1.085	1.080
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secured	0.291	0.297	0.293	0.294	0.299	0.296	0.304	0.293
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Senior	-0.455	-0.440	-0.415	-0.396	-0.377	-0.373	-0.353	-0.333
	(0.044)	(0.053)	(0.070)	(0.087)	(0.076)	(0.080)	(0.097)	(0.121)
Covenant	3.599	3.585	3.610	3.591	3.512	3.507	3.517	3.507
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Syndicate	1.077	1.081	1.070	1.071	1.075	1.075	1.072	1.067
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.403	0.403	0.405	0.404	0.397	0.397	0.398	0.398
NOBS	14,450	14,277	14,123	13,842	15,495	15,428	15,227	15,070

Table 1.3: Default Risk and the Likelihood of Using Performance Pricing Loans

This table reports logistic regression results explaining the effect of default risk on the use of performance pricing provision. Dependent variable is a dummy, which equals one if the loan spread is tied to a performance measure, and zero otherwise. *Default index* is a rank score based on all five measures of default risk: credit rating, Retstd, CFstd, Zscore and Oscore. Higher value of default index denotes higher default risk. Higher values of *Accrual Quality* variables (DD_AQ10 and MDD_AQ10) indicate poorer accounting quality. Standard errors are clustered at firm level. P-values are reported in parentheses below each coefficient estimate.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DD_AQ10	-3.245	-2.864	-2.981	-3.234	-3.112	-2.622	
	(0.007)	(0.016)	(0.013)	(0.008)	(0.010)	(0.027)	
MDD_AQ10							-2.334
							(0.020)
Credit rating	0.266						
	(0.010)						
Retstd		-2.308					
		(0.000)					
CFstd			-4.260				
			(0.000)				
Zscore				-0.005			
				(0.747)			
Oscore					-1.086		
					(0.006)		
Default index						-1.707	-1.586
						(0.000)	(0.000)
Firmsize	-0.185	-0.175	-0.186	-0.159	-0.094	-0.158	-0.172
	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.000)	(0.000)
ROA	2.852	2.567	3.027	2.916	2.852	2.410	2.308
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market-to-book	-0.070	-0.047	-0.026	-0.052	-0.064	-0.082	-0.071
	(0.091)	(0.249)	(0.535)	(0.295)	(0.117)	(0.046)	(0.095)
Ln(loan size)	0.341	0.339	0.350	0.343	0.341	0.333	0.341
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity	0.112	0.106	0.103	0.108	0.104	0.104	0.103
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Revolver	1.105	1.110	1.124	1.115	1.114	1.103	1.102
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secured	0.326	0.341	0.294	0.289	0.293	0.358	0.353
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Senior	-0.481	-0.475	-0.479	-0.455	-0.442	-0.497	-0.452
	(0.034)	(0.036)	(0.033)	(0.044)	(0.051)	(0.027)	(0.048)
Covenant	3.609	3.595	3.604	3.601	3.577	3.604	3.614
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Syndicate	1.094	1.074	1.067	1.077	1.029	1.081	1.075
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.404	0.405	0.405	0.403	0.404	0.406	0.407
NOBS	14,450	14,450	14,450	14,450	14,450	14,450	14,123

Table 1.4: Effect of Financial Restatements on the Probability of Using Performance Pricing

This table examines the effect of financial restatement on use of performance pricing loans. Dependent variable is a performance pricing dummy. *Post-restatement* is a dummy which equals one if the loan is issued after financial restatement, and zero otherwise. In the sample of six-year window [-3 yr, +3 yr], we includes all the loans issued three years before and three years after financial restatement. By the same token, eight-year window [-4 yr, +4 yr] sample includes all the loans issued four years before and four years after financial restatement. All other variables are as defined in Appendix A. Standard errors are clustered at firm level. P-values are reported in parentheses below each coefficient estimate.

	[-3 yr, +3 yr]		[-4 yr, +4 yr]	
	(1)	(2)	(3)	(4)
Post-restatement	-0.333	-0.232	-0.371	-0.316
	(0.068)	(0.262)	(0.017)	(0.074)
DD_AQ10		3.869		1.477
		(0.490)		(0.752)
Default index		-1.364		-1.441
		(0.207)		(0.113)
Firmsize	-0.184	-0.117	-0.154	-0.062
	(0.039)	(0.292)	(0.056)	(0.536)
ROA	3.790	3.445	4.070	3.375
	(0.005)	(0.020)	(0.000)	(0.015)
Market-to-book	-0.104	-0.076	-0.082	-0.042
	(0.450)	(0.658)	(0.455)	(0.769)
Ln(loan size)	0.278	0.260	0.249	0.237
	(0.013)	(0.064)	(0.008)	(0.038)
Maturity	0.209	0.271	0.217	0.275
	(0.000)	(0.000)	(0.000)	(0.000)
Revolver	1.526	1.766	1.605	1.747
	(0.000)	(0.000)	(0.000)	(0.000)
Secured	0.200	0.319	0.104	0.176
	(0.311)	(0.185)	(0.544)	(0.392)
Senior	1.878		2.084	
	(0.121)		(0.072)	
Covenant	4.675	5.339	4.676	5.267
	(0.000)	(0.000)	(0.000)	(0.000)
Syndicate	0.786	0.759	0.773	0.575
	(0.035)	(0.098)	(0.008)	(0.087)
Pseudo-R^2	0.400	0.431	0.409	0.423
NOBS	1,423	1,017	1,914	1,391

Table 1.5: Effect of Prior Lending Relationship on the Use of Performance Pricing Loans

In this table, we estimate two step instrumental variable regressions to examine the effect of bank-borrower prior lending relationship on the likelihood of using performance pricing loans. *Strength of bank-borrower prior lending relation($)* or *(N)* is computed as the dollar amount or the number of loans arranged by a particular lead bank and its predecessors for a firm during the previous 5 years divided by the total dollar amount or the number of loans borrowed by the firm during the same period, respectively. To address the endogenous matching between borrowers and lenders that affects prior lending relationship, we first regress *the strength of bank-borrower prior lending relation($)* or *(N)* on a few instrumental variables, including firm size, ROA, asset tangibility, and a dummy variable for accessing the public debt market. Predicted values of the *strength of prior lending relation($)* or *(N)* are then used in the second stage logistic models to explain the choice of using performance pricing loans. The results of the second stage logistic models are reported below. All other variables are as defined in Appendix A. Standard errors are clustered at firm level. P-values are reported in parentheses below each coefficient estimate.

Variable	(1)	(2)	(3)	(4)
Strength of bank-borrower prior lending relation ($)	11.679	12.595		
	(0.048)	(0.036)		
Strength of bank-borrower prior lending relation (N)			12.303	13.183
			(0.035)	(0.025)
DD_AQ10	-3.276		-3.254	
	(0.049)		(0.051)	
MDD_AQ10		-2.233		-2.207
		(0.081)		(0.084)
Default index	-1.605	-1.507	-1.614	-1.517
	(0.000)	(0.000)	(0.000)	(0.000)
Firmsize	0.013	0.013	0.081	0.085
	(0.881)	(0.883)	(0.464)	(0.448)
ROA	-1.831	-2.219	-2.099	-2.477
	(0.397)	(0.312)	(0.329)	(0.255)
Market-to-book	-0.070	-0.065	-0.071	-0.066
	(0.211)	(0.269)	(0.206)	(0.263)
Ln(loan size)	0.227	0.231	0.227	0.231
	(0.000)	(0.000)	(0.000)	(0.000)
Maturity	0.141	0.139	0.141	0.139
	(0.000)	(0.000)	(0.000)	(0.000)
Revolver	1.173	1.175	1.172	1.174
	(0.000)	(0.000)	(0.000)	(0.000)
Secured	0.267	0.259	0.270	0.262
	(0.003)	(0.005)	(0.003)	(0.004)
Senior	-0.763	-0.705	-0.764	-0.707
	(0.004)	(0.009)	(0.004)	(0.009)
Covenant	3.786	3.804	3.787	3.805
	(0.000)	(0.000)	(0.000)	(0.000)
Syndicate	1.015	1.007	1.014	1.006
	(0.000)	(0.000)	(0.000)	(0.000)
Industry dummy & year dummy	Yes	Yes	Yes	Yes
Pseudo-R^2	0.395	0.396	0.395	0.396
NOBS	9,763	9,527	9,763	9,527

Table 1.6: Heckman Probit Model

This table presents Heckman probit regression results explaining the choice of accounting based versus rating based performance pricing loans conditional on the use of performance pricing loans. We examine the effect of accounting quality. Columns (1) and (3) report the results of the selection models in which the choice of using performance pricing loan is examined. Columns (2) and (4) report the results of the probit model that evaluate the choices of using accounting based versus debt rating based performance pricing loan. All variables are as defined in Appendix A. Standard errors are clustered at firm level. P-values are reported in parentheses below each coefficient estimate.

	(1) PP v.s. non-PP	(2) Accounting based PP v.s. Debt rating based PP	(3) PP v.s. non-PP	(4) Accounting based PP v.s. Debt rating based PP
DD_AQ10	-2.002	-4.998		
	(0.040)	(0.054)		
MDD_AQ10			-1.557	-6.015
			(0.036)	(0.005)
Strength of bank-borrower	7.372	27.154	7.704	29.547
prior lending relation ($)	(0.011)	(0.000)	(0.010)	(0.000)
Default index	-0.924	2.630	-0.832	2.845
	(0.000)	(0.000)	(0.000)	(0.000)
Rating dummy		-1.413		-1.375
		(0.000)		(0.000)
Firmsize	0.013	-0.386	0.007	-0.384
	(0.763)	(0.001)	(0.878)	(0.001)
ROA	-1.292	-9.818	-1.446	-10.634
	(0.232)	(0.000)	(0.192)	(0.000)
Market-to-book	-0.049	-0.119	-0.042	-0.093
	(0.131)	(0.110)	(0.215)	(0.246)
Ln(loan size)	0.123	-0.205	0.129	-0.201
	(0.000)	(0.002)	(0.000)	(0.003)
Maturity	0.084	0.133	0.081	0.133
	(0.000)	(0.000)	(0.000)	(0.000)
Revolver	0.640	-0.050	0.634	-0.077
	(0.000)	(0.647)	(0.000)	(0.489)
Secured	0.147	1.200	0.147	1.258
	(0.003)	(0.000)	(0.004)	(0.000)
Senior	-0.186	0.000	-0.179	0.017
	(0.175)	(0.999)	(0.195)	(0.956)
Covenant	2.229	0.001	2.226	0.021
	(0.000)	(0.998)	(0.000)	(0.947)
Syndicate	0.563	-0.321	0.555	-0.382
	(0.000)	(0.185)	(0.000)	(0.126)
NOBS	9524		9299	

Table 2.1: Sample statistics

Our sample consists of 793 randomly selected firms during 1996 to 2005. For each sample firm, we examine its 10-K filling at each fiscal year end and collect the following information: whether a firm has a line of credit, whether a firm draws down its line of credit, what the drawdown rate is, and whether a firm violates any financial or general covenants of its debt contracts.

Variable	N	Mean	Median	STD
Having credit lines dummy	6859	0.831	1.000	0.375
Drawdown credit lines dummy	6777	0.526	1.000	0.499
Covenant violation dummy	6859	0.069	0.000	0.253
Asset ($ billion)	5656	1.535	0.277	3.754
Leverage	5704	0.243	0.234	0.196
Market-to-book	5539	1.862	1.442	1.275
ROA	5640	0.097	0.118	0.144
Tangibility	5656	0.296	0.214	0.239
Zscore	5318	4.213	3.085	4.758

Table 2.2: Univariate analysis on drawdown rate, predicted market rate, and contract rate on the line of credit

This table reports univariate results on drawdown rate, predicted market rate, and contract rate on the line of credit (LC) being drawn down and the new LC issued after the drawdown. All rates are expressed as basis points over LIBOR rate. T-tests and M-tests are used to test the null hypothesis that the mean and median difference is significantly different from zero respectively. P-values of these tests are reported in parentheses. ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

Panel A: Summary statistics

	N	Min	Max	Mean	Median	STD
Contract rate on LC being drawn down	804	15.00	580.00	174.59	150.00	106.86
Drawdown rate	804	2.38	765.23	195.70	175.00	134.36
Predicted (imputed) market rate	631	4.35	479.48	223.10	221.66	87.79
Contract rate on LC after drawdown	606	27.50	580.00	177.02	150.00	106.87

Panel B: Difference between drawdown rate and predicted market rate

	N	Mean	Median
(Drawdown rate – Predicted market rate)	631	-25.05*** (<.0001)	-40.85*** (<.0001)
(Drawdown rate – Contract rate on LC being drawn down)	804	21.11*** (<.0001)	0.00 (1.0000)
(Drawdown rate – Contract rate on LC issued after drawdown)	606	3.80 (0.3771)	2.00 (0.2164)

Table 2.3: Effect of bank reputation and prior lending relation on drawdown rate: univariate analysis

This table reports the univariate analysis of the difference between drawdown rate and predicted market rate (Drawdown rate – Predicted market rate) conditional on bank reputation and prior lending relation. Bank reputation is considered high if lead bank's market share is above the sample median, and considered lower otherwise. Bank-borrower prior lending relation is considered strong if the percentage of the amount of loans a firm borrowed from a particular bank during the previous five years is above the sample median, and considered weak otherwise. T-test, M-test, and F-test, and Z-test are used to test the null hypothesis that the mean, median, difference in mean, and difference in median is significantly difference from zero respectively. P-values of these tests are reported in parentheses. ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

		N	Mean	Median
Bank reputation	High	223	-37.97*** (<.0001)	-54.39*** (<.0001)
	Low	231	-25.19*** (0.0085)	-47.47*** (0.0024)
	Difference		-12.78 (0.3339)	-7.92 (0.5760)
Bank-borrower prior lending relation	Strong	225	-62.60*** (<.0001)	-73.79*** (<.0001)
	Weak	229	-0.88 (0.9226)	-11.53 (0.2904)
	Difference		-61.72*** (<.0001)	-62.26*** (<.0001)
Existence of prior lending relation	Yes	305	-50.35*** (<.0001)	-62.66*** (<.0001)
	No	149	7.18 (0.5326)	-4.11 (0.8699)
	Difference		-57.53*** (<.0001)	-58.55*** (<.0001)

Table 2.4: Effect of bank reputation and prior lending relation on the likelihood of drawdown and the drawdown rate: Heckman selection models

This table reports the results of Heckman selection models examining the effect of bank reputation and prior lending relation on the likelihood of drawdown and the drawdown rate. The dependent variable in the selection model is a binary variable that is equal to one if a borrower draws down its line of credit at a fiscal year end, and zero otherwise. Conditional on the drawdown, we examine how bank reputation and prior lending relation affect the difference between drawdown rate and the predicted market rate. *Covenant violation* is a dummy variable, which equals one if there is covenant violation in the drawdown year, and zero otherwise. High bank reputation dummy is equal to one if lead bank's market share is above the sample median, and zero otherwise. Strong lending relation dummy is equal to one if lead bank-borrower prior lending relation is above the sample median, and zero otherwise. All other variables are as defined in Appendix B. P-values are reported in parentheses below each coefficient estimate.

Panel A: Dependent variable is a dummy variable for drawdown or not

				Correct for endogenous choice of banks		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
High bank reputation dummy	-0.032			-0.033	0.095	
	(0.710)			(0.702)	(0.252)	
Strong lending relation dummy		-0.025		-0.026		-0.011
		(0.753)		(0.744)		(0.894)
Existence of prior lending relation			-0.159			
			(0.081)			
Cash flow	0.785	0.782	0.821	0.798	0.669	0.726
	(0.216)	(0.218)	(0.196)	(0.210)	(0.293)	(0.253)
Cash holding	-4.440	-4.426	-4.409	-4.432	-4.503	-4.483
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash flow × Cash holding	-6.591	-6.567	-6.450	-6.588	-6.326	-6.504
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)
Large firm	-1.023	-1.030	-1.008	-1.021	-1.010	-0.992
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Investment grade	-0.056	-0.064	-0.050	-0.057	-0.091	-0.080
	(0.554)	(0.492)	(0.587)	(0.548)	(0.329)	(0.392)
Market-to-book	0.000	0.000	-0.006	0.000	0.000	0.001
	(0.993)	(0.998)	(0.903)	(1.000)	(0.992)	(0.989)

Panel B: Dependent variable is the drawdown rate minus the predicted market rate

Variable	(1)	(2)	(3)	(4)	Correct for endogenous choice of banks (5)	(6)
High bank reputation dummy	21.741			18.370	-7.269	
	(0.102)			(0.159)	(0.551)	
Strong lending relation dummy		-53.948		-52.962		-58.485
		(0.000)		(0.000)		(0.000)
Existence of prior lending relation			-54.486			
			(0.000)			
Covenant violation	53.930	34.848	37.296	37.201	50.915	33.922
	(0.007)	(0.082)	(0.062)	(0.063)	(0.012)	(0.088)
First drawdown dummy	11.172	12.359	14.689	11.710	12.113	12.735
	(0.356)	(0.297)	(0.217)	(0.323)	(0.318)	(0.280)
Log(assets)	-0.624	2.203	2.280	-0.167	2.380	2.429
	(0.945)	(0.800)	(0.793)	(0.985)	(0.790)	(0.779)
Market-to-book	2.690	-3.019	-4.599	-1.852	1.255	-2.194
	(0.772)	(0.741)	(0.617)	(0.839)	(0.892)	(0.809)
Leverage	163.093	161.031	176.423	158.787	166.290	158.760
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-174.172	-201.397	-183.949	-196.918	-180.848	-199.451
	(0.019)	(0.006)	(0.012)	(0.007)	(0.015)	(0.006)
Tangibility	31.241	47.913	45.302	42.857	39.314	43.656
	(0.298)	(0.102)	(0.123)	(0.146)	(0.192)	(0.134)
Zscore	-1.861	0.334	0.245	-0.062	-1.404	-0.029
	(0.608)	(0.925)	(0.945)	(0.986)	(0.699)	(0.993)
Log(loan maturity)	-30.817	-34.752	-37.681	-34.032	-31.798	-35.227
	(0.029)	(0.012)	(0.007)	(0.014)	(0.025)	(0.011)
Log(loan size)	-27.385	-24.665	-24.164	-25.279	-26.248	-24.755
	(0.002)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)
Performance pricing	-9.184	-5.048	-4.306	-8.365	-4.309	-5.738
	(0.559)	(0.740)	(0.778)	(0.586)	(0.783)	(0.705)
Loan purpose & industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Inverse Mills Ratio	3.879	6.400	9.763	6.317	4.510	9.685
	(0.841)	(0.734)	(0.611)	(0.738)	(0.817)	(0.612)
NOBS	1,206	1,206	1,206	1,206	1,184	1,184

Table 2.5: Effect of bank reputation and prior lending relation in the presence of high versus low information asymmetry

This table reports the results of Heckman selection models examining the effect of bank reputation and prior lending relation on the likelihood of drawdown and the drawdown rate, conditional on information asymmetry. The dependent variable in the selection model is a binary variable that is equal to one if a borrower draws down its line of credit at a fiscal year end, and zero otherwise. Conditional on the drawdown, we examine how bank reputation and prior lending relation affect the difference between drawdown rate and the predicted market rate. Information asymmetry is proxied by firms' access to public debt market and stock return volatility. No public debt dummy is equal to one if a firm does not have any type of S&P debt rating available in the Compustat database, and zero otherwise. High return volatility dummy is equal to one for firms with stock return volatility above the sample median of a particular year, and zero otherwise. *Covenant violation* is a dummy variable, which equals one if there is covenant violation in the drawdown year, and zero otherwise. High bank reputation dummy is equal to one if lead bank's market share is above the sample median, and zero otherwise. Strong lending relation dummy is equal to one if lead bank-borrower prior lending relation is above the sample median, and zero otherwise. All other variables are as defined in Appendix B. P-values are reported in parentheses below each coefficient estimate.

Panel A: Dependent variable is a dummy variable for drawdown or not

Variable	(1)	(2)	(3)	(4)
High bank reputation dummy	0.058	-0.037		
	(0.680)	(0.743)		
Strong lending relation dummy			-0.146	0.058
			(0.273)	(0.599)
No public debt dummy	0.649		0.516	
	(0.000)		(0.000)	
High return volatility dummy		0.043		0.171
		(0.722)		(0.142)
High bank reputation×No public debt	-0.098			
	(0.572)			
Strong lending relation×No public debt			0.173	
			(0.308)	
High bank reputation×High return volatility		0.051		
		(0.764)		
Strong lending relation×High return volatility				-0.231
				(0.169)
Cash flow	0.744	0.574	0.737	0.595
	(0.243)	(0.381)	(0.247)	(0.363)
Cash holding	-4.915	-4.450	-4.918	-4.408
	(0.000)	(0.000)	(0.000)	(0.000)
Cash flow × Cash holding	-6.717	-6.224	-6.767	-6.180
	(0.004)	(0.008)	(0.004)	(0.008)
Large firm	-0.815	-1.015	-0.808	-1.015
	(0.000)	(0.000)	(0.000)	(0.000)
Investment grade	0.208	-0.050	0.199	-0.057
	(0.050)	(0.599)	(0.058)	(0.545)
Market-to-book	-0.003	0.000	-0.003	-0.003
	(0.957)	(0.992)	(0.955)	(0.948)

Panel B: Dependent variable is the drawdown rate minus the predicted market rate

Variable	(1)	(2)	(3)	(4)
High bank reputation dummy	14.064	8.838		
	(0.545)	(0.624)		
Strong lending relation dummy			-17.571	-24.228
			(0.416)	(0.152)
Same lead bank dummy				
No public debt dummy	-21.345		14.122	
	(0.408)		(0.495)	
High return volatility dummy		37.479		73.810
		(0.032)		(0.000)
High bank reputation×No public debt	11.500			
	(0.678)			
Strong lending relation×No public debt			-51.794	
			(0.046)	
High bank reputation×High return volatility		28.583		
		(0.222)		
Strong lending relation×High return volatility				-50.942
				(0.030)
Covenant violation	55.540	47.714	34.005	30.066
	(0.006)	(0.017)	(0.089)	(0.130)
First drawdown	9.671	10.404	10.950	10.157
	(0.426)	(0.393)	(0.354)	(0.396)
Log(assets)	-3.875	5.159	1.228	7.417
	(0.675)	(0.575)	(0.889)	(0.401)
Market-to-book	2.119	0.392	-2.783	-4.481
	(0.820)	(0.967)	(0.759)	(0.627)
Leverage	155.085	167.754	152.995	150.269
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-172.647	-125.203	-205.152	-133.272
	(0.020)	(0.096)	(0.005)	(0.071)
Tangibility	29.356	27.254	39.550	40.649
	(0.329)	(0.366)	(0.180)	(0.168)
Zscore	-2.050	-0.203	0.472	0.731
	(0.574)	(0.955)	(0.895)	(0.839)
Log(loan maturity)	-30.222	-20.622	-38.439	-28.144
	(0.034)	(0.160)	(0.006)	(0.051)
Log(loan size)	-27.310	-29.903	-25.548	-26.778
	(0.002)	(0.001)	(0.003)	(0.002)
Performance pricing	-8.917	-6.738	-0.634	-5.786
	(0.570)	(0.675)	(0.967)	(0.711)
Loan purpose & industry dummy	Yes	Yes	Yes	Yes
Inverse Mills Ratio	8.110	12.192	5.319	15.167
	(0.691)	(0.536)	(0.789)	(0.434)
NOBS	1,206	1,147	1,206	1,147

Table 2.6: Summary statistics of bank loans issued before and after the drawdown events

Our sample consists of 2,065 Dealscan loans issued by 345 firms from 1990 to 2007 that have data available in Compustat and CRSP. To be included in this sample, we require a firm to have at least one line of credit before and after the drawdown event. All variables are as defined in Appendix B.

	N	Mean	Median	STD
Loan spread (basis points)	1853	155.06	125.00	110.82
Secured dummy	1247	0.67	1.00	0.47
# of financial Covenants	2065	1.37	1.00	1.49
# of general Covenants	2065	2.82	2.00	3.03
# of Covenants	2065	4.19	4.00	4.17
# of lenders	2064	7.66	5.00	7.73
Upfront fee (basis points)	381	46.97	25.00	52.44
Annual fee (basis points)	583	18.14	12.50	27.59
Loan Maturity (months)	1894	42.49	41.85	22.78
Loan size ($ million)	2065	249.57	130.00	387.08
Performance pricing dummy	2065	0.45	0.00	0.50

Table 2.7: Effect of drawdown events on price and non-price contract terms of lines of credit

This table reports regression results explaining the effect of drawdown on various contract terms of credit facilities. Model (1) and (2) are OLS regressions with Log(loan spread) and Log(maturity) as the dependent variables, respectively. Model (3) is a Probit regression explaining the probability of a facility being secured. *Post-drawdown* is a dummy variable, which equals one if a facility is issued after the first drawdown year, and zero otherwise. *Covenant violation* is a dummy variable, which equals one if a firm violates its debt covenant in a particular year, and zero otherwise. All other variables are as defined in Appendix B. P-values are reported in parentheses below each coefficient estimate.

	(1) Log(loan spread)	(2) Log(maturity)	(3) Secured dummy
Post-drawdown	0.1901	-0.0648	0.4432
	(0.000)	(0.151)	(0.001)
Covenant violation	0.2353	-0.0992	0.7440
	(0.000)	(0.159)	(0.004)
Log(assets)	-0.1684	-0.1435	-0.1884
	(0.000)	(0.000)	(0.003)
Market-to-book	-0.1228	-0.0662	-0.0017
	(0.000)	(0.019)	(0.984)
Leverage	1.0760	0.2757	1.9995
	(0.000)	(0.005)	(0.000)
ROA	-1.0918	0.1841	-1.1883
	(0.000)	(0.321)	(0.071)
Tangibility	-0.1902	0.0590	-0.3117
	(0.016)	(0.496)	(0.220)
Cash flow volatility	0.6537	-1.1343	2.1663
	(0.204)	(0.041)	(0.220)
Zscore	0.0272	0.0091	0.0040
	(0.000)	(0.206)	(0.854)
Log(loan maturity)	0.0863		0.3254
	(0.001)		(0.000)
Log(loan size)	-0.1206	0.2149	-0.2939
	(0.000)	(0.000)	(0.000)
Performance pricing	-0.0196	0.2308	-0.3596
	(0.581)	(0.000)	(0.005)
Term Spread	0.1009	-0.0790	0.0603
	(0.000)	(0.002)	(0.397)
Credit spread	-0.1917	0.0910	0.0143
	(0.029)	(0.345)	(0.959)
Loan purpose & industry dummy	Yes	Yes	Yes
NOBS	1258	1333	899
Adj R^2 or Pseudo R^2	0.5079	0.2332	0.2714

Table 2.8: Effect of drawdown events on the price and non-price contract terms of lines of credit: the moderate effect of bank reputation and prior lending relation

This table reports regression results examining how bank reputation and prior lending relation moderate the effect of the drawdown events on various contract terms of credit facilities. Model (1) and (2) are OLS regressions with Log(loan spread) and Log(maturity) as the dependent variables, respectively. Model (3) is a Probit regression explaining the probability of a facility being secured. *Post-drawdown* is a dummy variable, which equals one if the line of credit is initiated after the first drawdown, and zero otherwise. High bank reputation dummy is equal to one if lead bank's market share is above the sample median, and zero otherwise. Strong lending relation dummy is equal to one if lead bank-borrower prior lending relation is above the sample median, and zero otherwise. *Covenant violation* is a dummy variable, which equals one if a firm violates its debt covenant in a particular year, and zero otherwise. All other variables are as defined in Appendix B. P-values are reported in parentheses below each coefficient estimate.

	Log(loan spread)		Log(maturity)		Secured dummy	
	(1)	(2)	(3)	(4)	(5)	(6)
High bank reputation	0.377		-0.027		0.910	
	(0.000)		(0.768)		(0.000)	
Post-drawdown	0.342	0.116	-0.103	-0.044	0.730	0.369
	(0.000)	(0.077)	(0.151)	(0.542)	(0.000)	(0.069)
High bank reputation × Post-drawdown	-0.376		0.042		-0.897	
	(0.000)		(0.677)		(0.001)	
Strong lending relation		-0.185		0.086		-0.054
		(0.026)		(0.337)		(0.824)
Strong lending relation × Post-drawdown		0.089		-0.077		-0.113
		(0.331)		(0.435)		(0.678)
Covenant violation	0.234	0.250	-0.050	-0.050	0.675	0.803
	(0.001)	(0.001)	(0.532)	(0.533)	(0.019)	(0.006)
Log(assets)	-0.184	-0.185	-0.164	-0.163	-0.243	-0.235
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Market-to-book	-0.129	-0.121	-0.051	-0.052	-0.082	-0.051
	(0.000)	(0.000)	(0.104)	(0.102)	(0.382)	(0.574)
Leverage	0.855	0.875	0.222	0.219	2.106	2.110
	(0.000)	(0.000)	(0.060)	(0.064)	(0.000)	(0.000)
ROA	-1.231	-1.235	0.221	0.227	-0.611	-0.687
	(0.000)	(0.000)	(0.370)	(0.357)	(0.431)	(0.374)
Tangibility	-0.190	-0.183	0.003	0.002	-0.266	-0.190
	(0.027)	(0.033)	(0.977)	(0.982)	(0.347)	(0.498)
Cash flow volatility	1.119	0.924	-1.279	-1.265	1.968	1.152
	(0.063)	(0.127)	(0.049)	(0.051)	(0.316)	(0.544)
Zscore	-0.009	-0.005	-0.003	-0.003	-0.015	-0.010
	(0.419)	(0.612)	(0.825)	(0.780)	(0.672)	(0.759)
Log(loan maturity)	0.098	0.099			0.395	0.386
	(0.000)	(0.000)			(0.000)	(0.000)
Log(loan size)	-0.106	-0.099	0.225	0.226	-0.297	-0.256
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Performance pricing	-0.018	-0.012	0.236	0.236	-0.450	-0.457
	(0.632)	(0.750)	(0.000)	(0.000)	(0.002)	(0.002)
Term Spread	0.098	0.102	-0.078	-0.078	0.088	0.095
	(0.000)	(0.000)	(0.004)	(0.004)	(0.261)	(0.222)
Credit spread	-0.254	-0.245	0.163	0.163	-0.081	-0.099
	(0.007)	(0.009)	(0.119)	(0.119)	(0.791)	(0.743)
Loan purpose & industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
NOBS	1073	1073	1128	1128	753	753
Adj R^2 or Pseudo R^2	0.509	0.505	0.244	0.244	0.284	0.273

Table 3.1: Sample statistics

This table reports summary statistics of our sample. The sample includes EBITDA based performance pricing loans, rating based performance pricing loans and non-performance pricing loans, which are issued by 4,279 firms during 1993 - 2007.

Variable	N	Mean	Median	Std Dev
Discretionary accruals				
Modified KLW (2005)	22030	-41.059	-1.651	557.223
Modified Jones (1991)	22088	-23.389	-0.456	574.547
TWW (1998)	22088	-23.579	-0.629	569.396
BS (2006)	20802	-9.295	0.085	685.977
Modified DD (2002)	17863	3.056	0.822	245.009
Performance pricing schedule				
Average slope	23553	0.513	0.000	0.796
Local slope	22746	0.409	0.000	0.732
Convexity	23528	0.462	0.000	0.772
Lender Characteristics				
High bank reputation dummy	15236	0.514	1.000	0.500
Existence of previous lending relation	15236	0.481	0.000	0.500
Borrower Characteristics				
Retained earnings	22310	494.942	30.855	2813.240
Assets	22368	2502.65	346.65	15142.76
Leverage	22415	0.277	0.253	0.229
Market-to-book	22359	1.890	1.453	1.786

Table 3.2: Effect of the slope and convexity of performance pricing schedule on discretionary accruals

These tables report regression results examining the effect of performance pricing schedule on discretionary accruals. We use different accrual measures here. 'Modified Jones (1991)' is based on Modified Jones model; 'Modified KLW (2005)' is based on Modified Kothari, Leon, Wasley (KLW) model; 'TWW (1998)' is based on Teoh, Welch, and Wong (1998) model; 'BS (2006)' is based on Ball and Shivakumar (2006) model; 'Modified DD (2002)' is based on Dechow and Dichev (2002) model. The sample includes Debt-to-EBITDA based performance pricing loans, Senior Debt Rating based performance pricing loans and non-performance pricing loans. All other variables are as defined in Appendix C. P-values are reported in parentheses below each coefficient estimate.

Panel A: Effect of average slope of performance pricing schedule on discretionary accruals

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
Average slope	13.344	12.794	12.140	19.640	2.505
	(0.010)	(0.008)	(0.018)	(0.002)	(0.293)
Retained earnings	-0.009	-0.055	-0.009	0.052	-0.021
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-25.282	-22.141	-24.962	-38.819	8.900
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-23.260	-28.389	-26.642	39.323	-23.590
	(0.197)	(0.090)	(0.136)	(0.089)	(0.007)
Market-to-book	-3.683	-7.263	-2.973	1.063	0.070
	(0.099)	(0.000)	(0.179)	(0.689)	(0.950)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	21,858	21,801	21,858	20,652	17,699
R-squared	0.023	0.107	0.024	0.048	0.071

Panel B: Effect of local slope of performance pricing schedule on discretionary accruals

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
Local slope	9.741	7.640	8.113	17.438	-2.734
	(0.088)	(0.149)	(0.151)	(0.012)	(0.297)
Retained earnings	-0.010	-0.057	-0.010	0.053	-0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-24.824	-21.364	-24.456	-39.441	8.502
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-26.058	-31.122	-30.144	40.208	-25.869
	(0.155)	(0.067)	(0.097)	(0.088)	(0.003)
Market-to-book	-3.930	-7.140	-3.217	0.608	-0.174
	(0.084)	(0.001)	(0.153)	(0.822)	(0.878)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	21,075	21,025	21,075	19,919	17,048
R-squared	0.024	0.110	0.025	0.049	0.077

Panel C: Effect of convexity of performance pricing schedule on discretionary accruals

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
Convexity	16.170	13.510	13.654	19.358	4.795
	(0.003)	(0.007)	(0.010)	(0.003)	(0.051)
Retained earnings	-0.009	-0.056	-0.009	0.052	-0.021
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-26.045	-22.713	-25.593	-39.485	8.591
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-22.404	-27.434	-25.761	40.956	-23.280
	(0.215)	(0.102)	(0.150)	(0.077)	(0.007)
Market-to-book	-3.774	-7.347	-3.073	0.903	0.150
	(0.091)	(0.000)	(0.165)	(0.734)	(0.893)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	21,833	21,779	21,833	20,631	17,683
R-squared	0.023	0.107	0.024	0.047	0.071

Table 3.3: Bank reputation, performance pricing schedule, and discretionary accruals

These tables report regression results examining how bank reputation affects the relationship between the performance pricing schedule and discretionary accruals. We use different accrual measures here. 'Modified Jones (1991)' is based on Modified Jones model; 'Modified KLW (2005)' is based on Modified Kothari, Leon, Wasley (KLW) model; 'TWW (1998)' is based on Teoh, Welch, and Wong (1998) model; 'BS (2006)' is based on Ball and Shivakumar (2006) model; 'Modified DD (2002)' is based on Dechow and Dichev (2002) model. The sample includes Debt-to-EBITDA based performance pricing loans, Senior Debt Rating based performance pricing loans and non-performance pricing loans. High bank reputation dummy is equal to one if lead bank's market share is above the sample median, and zero otherwise. All other variables are as defined in Appendix C. P-values are reported in parentheses below each coefficient estimate.

Panel A: Effect of PSD average slope on discretionary accruals conditional on bank reputation

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
High bank reputation dummy	35.731	32.347	34.705	10.012	9.456
	(0.001)	(0.001)	(0.001)	(0.439)	(0.079)
Average slope	21.544	20.726	21.712	10.006	-0.291
	(0.004)	(0.004)	(0.005)	(0.283)	(0.941)
Average slope × High bank reputation dummy	-22.123	-13.361	-22.823	-3.120	-4.516
	(0.034)	(0.180)	(0.036)	(0.812)	(0.407)
Retained earnings	-0.024	-0.071	-0.020	0.052	-0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-22.447	-22.914	-25.512	-26.349	13.918
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-46.287	-55.291	-49.456	48.865	-21.614
	(0.014)	(0.002)	(0.012)	(0.056)	(0.035)
Market-to-book	-7.285	-12.175	-6.261	0.219	-0.344
	(0.007)	(0.000)	(0.026)	(0.947)	(0.814)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	14,486	14,459	14,486	13,671	11,826
R-squared	0.046	0.190	0.043	0.061	0.099

Panel B: Effect of PSD local slope on discretionary accruals conditional on bank reputation

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
High bank reputation dummy	40.224	38.060	39.689	11.219	13.749
	(0.000)	(0.000)	(0.000)	(0.386)	(0.010)
Local slope	20.728	18.673	20.250	13.003	0.122
	(0.011)	(0.015)	(0.016)	(0.202)	(0.977)
Local slope × High bank	-34.560	-25.558	-36.268	-8.326	-15.993
reputation dummy	(0.004)	(0.023)	(0.003)	(0.576)	(0.009)
Retained earnings	-0.025	-0.073	-0.022	0.052	-0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-22.238	-22.248	-25.176	-26.165	13.199
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-49.100	-59.960	-53.208	49.268	-23.854
	(0.011)	(0.001)	(0.008)	(0.060)	(0.021)
Market-to-book	-7.275	-11.880	-6.292	0.189	-0.759
	(0.008)	(0.000)	(0.028)	(0.956)	(0.610)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	13,921	13,895	13,921	13,143	11,350
R-squared	0.049	0.198	0.046	0.063	0.108

Panel C: Effect of PSD convexity on discretionary accruals conditional on bank reputation

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
High bank reputation dummy	33.522	32.207	33.033	13.492	7.879
	(0.001)	(0.001)	(0.002)	(0.288)	(0.136)
Convexity	25.416	24.506	25.276	9.945	1.200
	(0.001)	(0.001)	(0.002)	(0.309)	(0.770)
Convexity × High bank	-19.898	-14.720	-21.735	-10.779	-2.116
reputation dummy	(0.058)	(0.141)	(0.047)	(0.411)	(0.699)
Retained earnings	-0.024	-0.071	-0.020	0.051	-0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-23.279	-23.824	-26.317	-26.108	13.772
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-46.010	-54.401	-49.061	49.379	-21.585
	(0.015)	(0.003)	(0.013)	(0.054)	(0.035)
Market-to-book	-7.371	-12.293	-6.376	0.036	-0.191
	(0.006)	(0.000)	(0.023)	(0.991)	(0.897)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	14,476	14,450	14,476	13,663	11,820
R-squared	0.047	0.190	0.044	0.061	0.099

Table 3.4: Prior lending relationship, performance pricing schedule, and discretionary accruals

These tables report regression results examining how prior lending relationship affects the relationship between the performance pricing schedule and discretionary accruals. We use different accrual measures here. 'Modified Jones (1991)' is based on Modified Jones model; 'Modified KLW (2005)' is based on Modified Kothari, Leon, Wasley (KLW) model; 'TWW (1998)' is based on Teoh, Welch, and Wong (1998) model; 'BS (2006)' is based on Ball and Shivakumar (2006) model; 'Modified DD (2002)' is based on Dechow and Dichev (2002) model. The sample includes Debt-to-EBITDA based performance pricing loans, Senior Debt Rating based performance pricing loans and non-performance pricing loans. *Existence of prior lending relation* is equal to one if the lead bank of the current loan has acted as a lead bank for a loan from the same firm during the prior 5 years, and zero otherwise. All other variables are as defined in Appendix C. P-values are reported in parentheses below each coefficient estimate.

Panel A: Effect of PSD average slope on discretionary accruals conditional on prior lending relation

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
Existence of prior lending relation	44.142	33.739	52.688	11.851	10.863
	(0.000)	(0.001)	(0.000)	(0.395)	(0.059)
Average slope	22.181	18.371	24.390	14.196	-0.355
	(0.005)	(0.015)	(0.003)	(0.148)	(0.932)
Average slope × Existence of	-24.695	-10.928	-29.649	-11.592	-4.839
prior lending relation	(0.020)	(0.281)	(0.007)	(0.383)	(0.382)
Retained earnings	-0.023	-0.070	-0.020	0.052	-0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-24.872	-24.641	-28.779	-26.609	13.349
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-45.561	-54.368	-49.665	49.601	-21.306
	(0.016)	(0.003)	(0.012)	(0.052)	(0.037)
Market-to-book	-6.637	-11.616	-5.567	0.414	-0.219
	(0.014)	(0.000)	(0.047)	(0.901)	(0.881)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	14,486	14,459	14,486	13,671	11,826
R-squared	0.047	0.190	0.044	0.061	0.099

Panel B: Effect of PSD local slope on discretionary accruals conditional on prior lending relation

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
Existence of prior lending relation	46.139	38.753	54.092	8.866	13.302
	(0.000)	(0.000)	(0.000)	(0.527)	(0.020)
Local slope	16.774	14.180	17.024	10.763	-2.400
	(0.049)	(0.080)	(0.055)	(0.313)	(0.589)
Local slope × Existence of prior lending relation	-27.370	-18.065	-30.815	-3.981	-10.414
	(0.022)	(0.110)	(0.013)	(0.790)	(0.092)
Retained earnings	-0.025	-0.072	-0.021	0.052	-0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-25.036	-24.375	-28.889	-26.570	12.466
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-48.042	-58.609	-53.078	49.797	-23.201
	(0.012)	(0.001)	(0.008)	(0.057)	(0.024)
Market-to-book	-6.565	-11.232	-5.537	0.357	-0.598
	(0.017)	(0.000)	(0.053)	(0.917)	(0.688)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	13,921	13,895	13,921	13,143	11,350
R-squared	0.049	0.198	0.046	0.063	0.107

Panel C: Effect of PSD convexity on discretionary accruals conditional on prior lending relation

Variable	Modified Jones (1991) (1)	Modified KLW (2005) (2)	TWW (1998) (3)	BS (2006) (4)	Modified DD (2002) (5)
Existence of prior lending relation	40.101	32.214	49.881	15.682	7.844
	(0.000)	(0.002)	(0.000)	(0.250)	(0.164)
Convexity	25.578	20.951	28.676	14.829	0.136
	(0.003)	(0.010)	(0.001)	(0.164)	(0.976)
Convexity × Existence of prior lending relation	-20.568	-9.586	-28.087	-18.411	-0.722
	(0.059)	(0.355)	(0.013)	(0.175)	(0.899)
Retained earnings	-0.024	-0.070	-0.020	0.052	-0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-25.519	-25.483	-29.473	-26.706	13.365
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-45.392	-53.509	-49.399	50.159	-21.372
	(0.016)	(0.003)	(0.012)	(0.050)	(0.037)
Market-to-book	-6.727	-11.718	-5.666	0.291	-0.084
	(0.012)	(0.000)	(0.043)	(0.930)	(0.954)
Industry dummy & year dummy	Yes	Yes	Yes	Yes	Yes
Observations	14,476	14,450	14,476	13,663	11,820
R-squared	0.047	0.190	0.044	0.061	0.099

Figure 1.1: Distribution of Performance Pricing Loans Over Time

This figure presents the percentage of performance pricing loans over time. *pploan_number* is measured as the number of performance pricing loans in a particular year as the fraction of the total number of loans issued in that year. *pploan_amount* is calculated as the total amount of performance pricing loans in a particular year divided by the total amount of loans issued in that year. Our sample includes 16,784 loans from Dealscan. Data in 2007 may be incomplete because we extract data from Dealscan at the end of 2007.