Special Purpose Entities and Bank Loan Contracting

Abstract

This study examines the relation between a firm's use of special purpose entities (SPEs) and its bank loan contracting. Although SPEs can serve many legitimate business purposes, they have been used improperly by sponsor firms to manipulate earnings and hide losses, resulting in higher information risk. We find that (1) the use of SPEs tends to be associated with unfavorable loan contracting terms, including higher loan rates, collateral requirements, and restrictive covenants, and (2) the above associations are more pronounced when the borrower firm has greater CEO pay–performance sensitivity (delta) and no prior loan relationship with the lender.

Keywords: *Special purpose entity; loan contracting; information risk; earnings management*.

JEL Code: *G21; M41*

Data Availability: *All data are available from the sources identified in the paper.*

1. Introduction

Companies have been using special purpose entities (SPEs) since the 1970s. SPEs can serve many legitimate business purposes, such as lowering financing costs, isolating financial risk, accessing segmented capital markets, and tax planning (Feng, Gramlich, and Gupta 2009; Lemmon, Liu, Mao, and Nini 2014). However, investigations of Enron and other corporate scandals reveal that SPEs have been improperly used by sponsor firms to hide debt, manage earnings, and achieve other financial reporting objectives.[1] SPEs can facilitate managerial opportunism in financial reporting for two main reasons. First, a sponsor company can avoid consolidating its SPEs in the financial statements and achieve managers' financial reporting goals through its transactions with the SPEs under its control. Second, the complex nature of SPEs can increase information uncertainty or opaqueness, which constrains the ability of investors and creditors to fully understand the sources of managers' earnings management.

Recent studies show evidence that financial reporting quality plays an important role in bank loan contracting (Beatty, Ramesh, and Weber 2002; Bharath, Sunder, and Sunder 2008; Costello and Wittenberg-Moerman 2011; Graham, Li, and Qiu 2008; Kim, Song, and Zhang 2011; Kim, Tsui, and Yi 2011). More specifically, these studies find that low reporting quality is associated with unfavorable loan terms, because it may impair lenders' ability to evaluate borrowers' default risk prior to contract initiation and increase their post-contract monitoring and renegotiation costs. In this study, we aim to provide systematic evidence on the effect of SPEs on the loan contracting terms of their sponsor firms. Specifically, our analysis focuses on whether and how banks take into account a borrower's

[1] For example, the Special Investigative Committee on Enron reported that Enron's transactions with certain SPEs "allowed Enron to conceal from the market very large losses resulting from Enron's merchant investments" (Powers 2002, 4).

use of SPEs when evaluating credit quality and/or determining both the price and non-price terms of loan contracts.

We are motivated to examine the debt market consequences of non-financial companies' SPE use in the context of bank loan contracting for several reasons. First, bank loans are a major source of external financing for companies around the world.[2] However, while it has examined SPEs sponsored by banks for mortgage or loan securitization, prior research has paid little attention to the potential impacts of SPE use on the costs of bank loans to *non-financial* sponsor firms. Second, banks use non-price terms in the loan contracts to facilitate the post-contract monitoring of borrower credit quality and its changes. To evaluate the effect of SPE use on non-price terms (in addition to the price term), our study provides evidence on whether banks tend to impose more stringent non-price terms in response to a borrower's SPE use. Third, Lemmon et al. (2014) find positive abnormal stock returns and zero bond returns to the initiation of asset securitization, a common type of SPEs, using a sample of non-financial firms. Focusing on sponsor firms' default (operation) risk, this finding can be viewed as evidence suggesting that asset securitization is beneficial to equity investors without hurting bond investors. Different from Lemmon et al. (2014), the primary purpose of our study is to investigate whether as an earnings management tool, the use of SPEs affects sponsor firms' *private debt* contracting through increasing the *information* risk faced by lenders. It should be noted, however, that compared with arms-length equity and bond investors, concentrated lenders such as commercial banks are generally more sophisticated and have privileged access to sponsors' inside information (e.g., Bharath et al. 2008; Kim et al. 2011b). One may therefore argue that SPE use does not

[2] In the United States, the amount of loan borrowing is much larger than the amount of equity and bond issuing (Graham, Li, and Qiu 2008). In 2013, the total volume of U.S. loans is $2,142 billion (Bloomberg 2014).

necessarily increase lenders' information risk, and thus has no significant impact on loan contracting terms. Therefore, it is an empirical question whether the use of SPEs matters to banks when contracting with SPE sponsor firms.

Using a large sample of bank loan contracts (with 11,088 loan facilities) with public non-financial companies from 1997 to 2008, we find that loans to the sponsor companies of SPEs are (1) charged at higher loan rates, (2) more likely to be secured by collateral, and (3) more likely to include covenant restrictions, compared with companies that do not use SPEs. Such findings suggest that banks and other private lenders perceive that firms with SPEs have higher credit risk or lower credit quality. We also perform an intertemporal analysis by examining the loans issued within a four-year window around (two years before and two years after) the initiation of SPEs for the sample of SPE sponsor firms. This intertemporal comparison reveals that SPE initiation increases loan rates and the likelihood of loans being subject to collateral requirements. In addition, to address potential endogeneity with respect to a firm's use of SPEs, we apply the propensity score matching (PSM) method. We find that our results are robust to the employment of the PSM method, alleviating the endogeneity concern.

Thus far, our findings suggest that for prospective private lenders such as banks, the costs associated with SPEs dominate the benefits. As discussed in prior studies (Feng et al. 2009; Lemmon et al. 2014), SPEs can provide benefits to sponsor firms, including lowered finance costs for SPE borrowings, tax savings, and access to segmented capital markets. In addition, by obtaining additional external financing, SPEs can increase the cash flows available to the sponsor firms for servicing debt repayments.[3] However, at the same time, SPEs can help managers hide liability off balance sheet, if not consolidated, and may

[3] Lemmon et al. (2014) find that the funds from the securitization largely pay down existing debt.

encourage managerial risk taking by converting safe assets, such as accounts receivable, into cash and using cash for risky projects. Therefore, it is not a priori obvious whether SPE usage increases or decreases default risk. However, by facilitating opportunistic earnings management, SPE activities are likely to reduce financial reporting quality (Dechow, Myers, and Shakespeare 2010) and consequently increase the information risk faced by lenders in estimating the sponsor firms' default risk and/or underlying cash flows (Bharath et al. 2008).

While it is challenging to separate the two dimensions of the credit risk (i.e., default risk and information risk) associated with borrowers' use of SPEs, we carry out subsample analyses to identify possible situations under which the effect of SPE usage on bank loan terms is more likely to hinge on information risk. First, prior studies find that the delta risk of managerial compensation is positively related to earnings management, which increases information risk, but negatively related to risk taking (Coles, Daniel, and Naveen 2006). We thus argue that for firms with higher delta risk of managerial compensation, the effect of SPE usage on bank loan contracting is more likely to hinge on information risk. Our empirical analyses show that the associations between SPE use and the various terms of bank loan contracting are more pronounced for sponsor firms with higher delta risk. Second, when SPE sponsor firms and their lenders have prior lending relationships, the lenders face lower information risk in the sense that they have prior knowledge about the borrowers' operations and SPE activities. In such a case, the lenders are more likely to overcome the information risk associated with borrowers' use of SPEs. The findings of our empirical analyses show that the impact of SPE usage on loan terms is mainly driven by firms with no prior relationship with their lenders. The above cross-sectional variations in the impact of SPE usage on loan contracting terms observed across different subsamples of SPE sponsor firms provide some direct evidence on SPEs' role in increasing information risk.

In addition to the subsample analyses discussed above, we perform a battery of additional analyses aimed to test the effect of SPE usage on loan contracting terms through the information risk channel. First, we include Standard & Poor's long-term issuer credit rating in the regression model as an additional control variable.[4] We find that SPE usage remains significantly associated with unfavorable loan terms even after controlling for credit ratings. Since rating agencies should have considered off balance sheet financing and the effect of SPE usage on default risk in setting credit ratings, information risk is likely to be an important driver of this significant relation observed between SPE usage and unfavorable loan terms. Second, we find a positive association between SPE usage and financial restatements, but no significant association between SPE usage and future credit default, suggesting that SPE usage is more likely to be associated with higher information risk than default risk. Lastly, we specifically test the effect of asset securitization——a specific, but common type of SPEs——on loan terms. The results show that asset securitization is associated with unfavorable loan terms after controlling for the amount of off balance sheet borrowings through securitizations, suggesting that asset securitization increases banks' information risk.

Our study contributes to the literature in two ways. First, it adds to the literature examining the economic consequences of SPE use by non-financial companies.[5] A recent study by Lemmon et al. (2014) documents zero bond market reactions and positive equity

[4] Since half of the firms in our sample do not have credit ratings, our sample will lose representativeness if we include credit ratings as a control variable in our main tests.
[5] Literature on the effect of SPEs mainly focuses on financial institutions (e.g., Chen, Liu, and Ryan, 2008; Downing, Jaffee, and Wallace 2009; Mian and Sufi 2009; Keys et al. 2010; Piskorski, Seru, and Vig 2010; Barth, Ormazabal, and Taylor; 2011; Nadauld and Weisbach 2012).

market reactions to the initiation of non-financial firms' asset securitization, suggesting that the use of SPEs benefits existing shareholders without hurting bondholders. Our study is one of the few which provides large-sample, evidence on the debt market consequences of *non-financial* companies' SPE activities in the context of loan contracting.

Second, our study contributes to the bank loan literature. We provide evidence that SPE use is an incrementally significant factor determining credit quality, particularly the information risk of the borrowing firms, over and beyond other borrower- and loan-specific factors that are known to affect the price and non-price terms of loan contracting.

Finally, our study has a policy implication. In 2009, the Financial Accounting Standards Board (FASB) issued FAS 166 and 167 to amend existing standards that guide the reporting of "special purpose entities" (FASB 2009a, b). Robert Herz, the then Chairman of the FASB claims that "[T]hese changes were proposed and considered to improve existing standards and to address concerns about companies who were stretching the use of off-balance sheet entities to the detriment of investors. The new standards eliminate existing exceptions, strengthen the standards relating to securitizations and special-purpose entities, and enhance disclosure requirements. They provide *better transparency* for investors about a company's activities and risks in these areas" (emphasis added).[6] Our findings suggest that SPEs provide managers with a convenient tool for obfuscating financial reporting, which in turn increases the information risk to prospective lenders, when evaluating the default risk of SPE sponsor firms. One way to alleviate the information risk associated with SPE usage is to require more sufficient disclosures of SPE activities in the financial statements, consistent with the FASB's goal of issuing the two statements (FAS 166 and 167) to improve financial reporting of SPEs.

[6] http://www.fasb.org/cs/ContentServer?pagename=FASB/FASBContent_C/NewsPage&cid=1176156240834.

The remainder of the paper is structured as follows. Section 2 develops our hypotheses. Section 3 describes our research design, including the measurement of SPE use and hypothesis testing procedures. Section 4 first explains sample selection procedures and then presents descriptive statistics on the major research variables. Section 5 provides the results of our empirical analyses, including main regressions, robustness tests, and additional tests. The final section concludes the paper.

2. Hypothesis Development

An SPE is a legally distinct entity with a limited life created by a sponsor company to carry out limited activities or transactions as specified in the contracts (Hartgraves and Benston 2002; Soroosh and Ciesielski 2004; Feng et al. 2009). SPEs have been used in various transactions, for example, leasing, asset securitization, throughput contracts, and joint venture research and development (R&D) arrangements (Soroosh and Ciesielski 2004). The formation of SPEs can bring real economic benefits to the sponsor firms for several reasons, as explained below.

First, since SPEs isolate and homogenize cash flows and business risks related to a specific class of assets, the sponsor can obtain external financing through SPEs at a lower cost (e.g., Soroosh and Ciesielski 2004; Dechow and Shakespeare 2009; Feng et al. 2009). Usually SPEs are bankruptcy remote from the sponsor firms' financial distress, and thus, the creditors of SPEs can avoid any deadweight costs associated with the bankruptcy of the sponsor firms, which in turn lowers the financing costs of SPEs (Ayotte and Gaon 2011; Lemmon et al. 2014).

Second, because SPEs are structured with very different risks from those of the sponsor firms, they can help sponsor firms access additional segments of the capital market and acquire additional sources of capital. For example, Lemmon et al. (2014) show that SPEs formed for securitization allow firms without the top commercial paper rating to gain access to the commercial paper market and firms with speculative-grade ratings to have access to the investment-grade bond market, which in turn contributes to lowering the financing costs of the sponsor firms.

Third, prior studies suggest that SPEs are usually created as flow-through entities (e.g., limited partnerships or limited liability companies), thus offering tax benefits to the sponsors (e.g., Beatty, Berger, and Magliolo 1995; Gupta and Mills 2002; Soroosh and Ciesielski 2004; Feng et al. 2009). In addition, SPEs formed for joint venture R&D arrangements allow firms with low marginal tax rates to effectively sell the benefit of the immediate tax deductibility of R&D to firms with high marginal tax rates, realizing tax benefits for both the sponsor firms and investors of the SPEs (Shevlin 1987; Beatty et al. 1995).

Lastly, SPE activities increase the fund available for serving debt repayment and interest payment. For example, SPEs formed to securitize long-term receivables provide the sponsor firms with an immediate source of cash and eliminate the risk of holding the receivables (Dechow et al. 2010). Lemmon et al. (2014) also find that funds from asset securitization largely pay down existing debt.

On the other hand, there are also negative economic consequences of SPE formation for the outside stakeholders of the sponsor firms, especially their creditors. First, the creditors of SPEs have a first-priority claim on the assets transferred to the SPEs, which effectively subordinates existing debt with respect to the securitized assets (Lemmon et al. 2014). For example, a sponsor firm's retained interest in securitized receivables is available to service on balance sheet debt only after the debt of the SPE has been paid off. Second, to lower financing costs, the sponsor firms usually transfer fairly low risk assets to the SPEs, which may result in more volatile assets on the balance sheets. Third, the increase in funds available may encourage managers to take more risk in their investment decisions. For example, SPEs formed for joint venture R&D arrangements provide the sponsor firms with more funding sources for their innovation activities (Beatty et al. 1995).

Lemmon et al. (2014) find positive abnormal stock and zero bond returns around the initiation of asset securitization. Their finding suggests that securitization via SPE usage benefits existing shareholders without hurting existing bondholders. Stated another way, this implies that the benefits of securitization dominate the associated costs to arms-length capital suppliers such as shareholders and bondholders. However, their study does not consider another potential cost, that is, the increase in *information risk* arising from SPE usage that outside capital suppliers, in general, and concentrated private lenders such as commercial banks, in particular, must face when evaluating the *default risk* of the sponsor firms. As shown in Duffie and Lando (2001), information risk or the transparency component of credit risk is an important part of credit risk, along with default risk.

Although originated to serve legitimate business purposes, SPEs have been used as an accounting tool for corporate managers to window-dress financial statements and manipulate earnings. For example, in a sale-leaseback transaction, the sponsor creates an SPE to borrow money and then the SPE uses the borrowed money to purchase the sponsor's long-term fixed asset at a price set by the sponsor. Then the sponsor leases the asset back from the SPE under the operating lease. This series of transactions facilitates the sponsor's earnings management. The sponsor has control over the price of the fixed asset sold to the SPE and thus can inflate its current-period reported earnings through the amount of gains recognized on the sale. In addition, the sponsor can control the timing and amount of the operating lease payments for leasing back the fixed asset from the SPE, which further facilitates earnings management by the sponsor. In a typical receivable securitization transaction, the sponsor sells a portion of the interests in its receivables to an SPE and retains the residual interest in the remaining receivables. The SPE sells the acquired receivables to a third party in exchange for a loan and pays the sponsor using cash proceeds from the loan. By treating securitizations as sales rather than collateral borrowings, the sponsor's balance sheet appears less risky. In addition, by inflating the value of the sold and retained interest in the receivables, the sponsor can recognize gains and manage earnings upward.

The collapse of Enron and other SPE-related corporate scandals provide evidence that companies hide debt and manage earnings by not consolidating SPEs into their financial statements (Yale, 2002; SEC, 2005).[7] Dechow and Shakespeare (2009) document that sponsors time securitization transactions to achieve financial reporting goals, such as lowering leverage and beating earnings thresholds. Dechow et al. (2010) find that firm managers use discretion within fair value accounting rules (e.g., choosing the discount rate) to report larger gains from securitization, thus obtaining higher compensation. In addition, the complex nature of SPEs makes it hard for investors/creditors to understand the sources of earnings management. Dechow et al. (2010) find that even informed and independent

[7] Before 2003, U.S. Generally Accepted Accounting Principles allowed a sponsor to exclude an SPE from its financial statements if third-party residual equity investment at risk equaled at least 3% of the SPE's total capitalization (FASB 1990). In response to the Enron scandal, in 2003 the FASB issued FIN No. 46(R) to require that variable interest entities be consolidated in the financial statements of the primary beneficiary (FASB 2003).

directors do not distinguish between securitization gains and other components of earnings when awarding CEO pay.[8]

In this study, we examine the impact of SPE use from the perspective of private lenders such as banks. While the predictions for the effect of SPEs on default risk are two-sided, the increase in information risk due to SPE usage should be associated with unfavorable loan contracting terms. SPEs provide firms with a tool for earnings management, which lowers the quality of financial reporting and increases the information risk faced by creditors in estimating a sponsor's future cash flows and assessing its credit quality. Previous theoretical and empirical studies have documented that lenders require compensation for borrower information risk, which is incremental to default risk (e.g., Duffie and Lando 2001; Easley and O'Hara 2004; Francis et al. 2005; Lambert, Leuz, and Verrecchia 2007; Bharath et al. 2008; Graham et al. 2008; Costello and Wittenberg-Moerman 2011; Kim et al. 2011b, 2011c). Bharath et al. (2008) find that banks charge lower interest rates to loans made to firms with higher accrual quality. Graham et al. (2008) show that borrowers are charged high loan rates after their financial statements are restated. Both Kim et al. (2011b) and Costello and Wittenberg-Moerman (2011) find that banks charge higher interest rates to borrowers with internal control weaknesses than those without.

Drawing on the above discussions, we predict that SPE use is more likely to be associated with higher loan interest rates, primarily due to its effect on increasing information risk. To test this prediction, we formally hypothesize the following in alternative form.

[8] By examining banks' asset securitization, Cheng, Dhaliwal, and Neamtiu (2011) find that securitizations increase information uncertainty, as reflected in higher bid–ask spreads and analyst forecast dispersion, compared to banks without such transactions and that information uncertainty increases with the amount of securitized assets. Dou, Liu, Richardson and Vyas (2014) find that investors recognized the increasing risk of securitized subprime and commercial mortgages as the recent financial crisis progressed, suggesting that the risk structure of securitization is opaque.

H1: *The use of SPEs is positively associated with a sponsor firm's loan interest rates, all else being equal.*

Compared with equity and bond investors, banks are generally more sophisticated, have privileged access to private information about the borrower, and have stronger information processing abilities (e.g., Bharath et al. 2008). In addition, since only a limited number of lenders are associated with private loans, post-contract monitoring is less subject to the free rider problem and thus more effective (Diamond 1984). This superior information access and effective ex post monitoring could reduce the adverse selection costs and mitigate the information uncertainty when contracting with borrowers with SPEs. One can therefore expect that, contrary to the prediction of H1, SPE use has no impact on loan pricing. Stated another way, the null hypothesis of no relation between SPE use and loan interest rate is credible.

Bank loan contracts include not only price terms (i.e., interest rates), but also non-price terms, such as collateral requirements and restrictive covenants. Commercial banks and other private lenders use non-price terms in loan contracts to monitor post-contract credit quality changes, mitigate information problems and agency conflicts, and control lenders' risk exposure. Previous studies show that lenders are more likely to require collateral for and impose restrictive covenants on loans to borrowers with higher default and information risks to facilitate post-contract monitoring and renegotiation (e.g., Berger and Udell 1990; Rajan and Winston 1995; Jimenez, Salas, and Saurina 2006; Bharath et al. 2008; Graham et al. 2008; Demiroglu and James 2010; Kim et al. 2011b, 2011c). To the extent that the use of SPEs increases the default and information risks of the sponsor firms, we expect SPE use to be positively associated with the likelihood of loans being secured by collateral and/or subject to restrictive covenants. In addition, private lenders may use non-price terms as a substitute for price terms when contracting with borrowers of high default/information risk. To provide systematic evidence on the impact of SPE usage on non-price loan terms, we test our second hypothesis in alternative form.

> **H2**: *The likelihoods of loans being secured by collateral and of loans being subject to restrictive covenants are greater for borrowers who use SPEs than for those who do not use SPEs, all else being equal.*

The predictions of H1 and H2 can be based on the effect of SPE usage on increasing either the borrower's default risk or information risk or both. An additional challenge is that SPE usage may simply represent off balance sheet liability, which lenders must take into account when evaluating borrowers' credit quality and, thus, should be associated with unfavorable loan terms. In an attempt to provide more direct evidence of the impact of SPE use on information risk, we identify potential situations under which the effect of SPE usage on bank loan terms is more likely to hinge on information risk than on default risk. If we observe significant cross-sectional differences in the SPE effect on loan terms or a stronger SPE effect in certain situations, to some extent it helps us rule out the possibility that SPE usage simply measures off balance sheet liability. In other words, if SPE usage only represents off balance sheet liability, we should not be able to identify situations under which SPE usage has no effect on loan contracting.

The finance literature suggests that higher CEO pay–performance sensitivity (delta) is associated with less managerial risk taking and more reporting opportunism (Core and Guay 2002; Bergstresser and Philippon 2006; Burns and Kedia 2006; Coles et al. 2006; Kim, Li, and Zhang 2011). The sensitivity of CEO wealth to stock price (delta) aligns the incentives of managers with the interests of shareholders because managers share gains and losses with shareholders (Coles et al. 2006). However, because managers are undiversified with respect to firm-specific wealth, they are more risk averse than diversified shareholders and a larger delta exposes managers to more risk and reduces their incentive to take on risky projects. Coles et al. (2006) find that a higher delta is associated with lower R&D expenditures, higher capital expenditures, and lower leverage. Then, in the context of our study, this suggests that the fund generated by SPEs is more likely to be used in debt repayment or invested in safer projects if the sponsor firms' managers have higher pay–performance sensitivity (delta), reducing the firms' default risk.

Another potential effect of an increased delta is that managers may have incentive to misreport to increase equity value. Bergstresser and Philippon (2006) find that the use of discretionary accruals to manipulate reported earnings is more pronounced at firms where the change in the CEO's potential total compensation is more sensitive to stock price changes (delta). Kim et al. (2011a) show evidence that managerial equity incentive captured by delta is positively associated with future stock price crash risk, an extreme outcome of earnings manipulation and bad news hoarding. Burns and Kedia (2006) find a positive relation between the CEO's portfolio delta and accounting restatement. Therefore, we expect that for SPE sponsor firms with greater pay–performance sensitivity, captured by delta, their lenders face even higher information risk/uncertainty associated with SPEs because the borrowers have stronger incentive to manipulate earnings and the SPEs provide them with a convenient tool for misreporting. Motivated by the information risk effect, we develop our third hypothesis in alternative form to examine the impact of SPE usage on price and non-price loan terms conditional on managerial pay–performance sensitivity.

> **H3**: *SPEs have a stronger impact on the price and non-price terms of loans borrowed by sponsor firms with greater managerial pay–performance sensitivity (delta), all else being equal.*

In loan contracting, the information friction caused by adverse selection and moral hazard can be mitigated if the leading lender has had a strong past relationship with the borrower, because borrower-specific information obtained through a prior lending relationship is largely durable and reusable (Boot 2000; Bharath et al. 2011). Bharath et al. (2011) find that the benefits of relationship lending in reducing information friction are more pronounced when there is greater information asymmetry between lenders and borrowers. To the extent that SPE usage increases information asymmetry between lenders and borrowers, we expect prior lending relationship to alleviate the impact of SPE usage on price and non-price loan terms. To show evidence on the impact of SPE usage on loan contracting conditional on a prior lending relationship, we test the following hypothesis in alternative form.

> **H4**: *SPEs have a stronger impact on the price and non-price terms of loans borrowed by sponsor firms that never had a prior lending relationship with their lenders, all else being equal.*

3. Research Design

3.1 Measurement of SPE Use

Following Feng et al. (2009), we measure a firm's use of SPEs by counting the limited partnerships, limited liability partnerships, limited liability companies, and trusts included in the list of subsidiaries and affiliates in Exhibit 21 of SEC Form 10-K on Edgar for each year. The acronyms *L.P.*, *LP*, *LLP*, *L.L.P.*, *LLC*, and *L.L.C.* are also included in the search. Our measure of SPE use is *NSPE*, which refers to the number of a borrowing firm's SPEs each year and is intended to capture a sponsor firm's intensity of SPE use.

By employing *NSPE* instead of the SPE proxies related to particular transactions, such as asset securitizations, we can conduct large-sample cross-sectional and intertemporal analyses in the bank loan market. Before Feng et al. (2009), studies that examine non-financial companies' SPEs used manually collected data for small samples to examine SPE use in particular transactions such as asset securitizations (Dechow et al., 2008) and R&D financing (Beatty et al., 1995). As Feng et al. (2009) argue, such small-sample or short-period analyses limit the ability to examine broader issues and to generalize results. By employing the number of SPEs as the proxy for the intensity of SPE use, we can investigate the broader issue of whether SPE use affects loan contracting terms, using a large sample.[9]

3.2 Tests of Hypotheses

To provide empirical evidence on the role of SPE use in loan pricing as hypothesized in H1 and H2, we specify the following regression model:

$$\begin{aligned} \textit{Loan Feature}_{ikt} = {} & \alpha_0 + \alpha_1 \textit{Log NSPE}_{it-1} + \alpha_2 \textit{Loan-specific Control}_{ikt} \\ & + \alpha_3 \textit{Borrower-specific Control}_{it-1} + \alpha_4 \textit{Economy-wide Control}_t \\ & + (\textit{Loan Purpose Indicators}_{ikt}) + (\textit{Year Indicators}_{it}) \\ & + (\textit{Industry Indicators}_{it-1}) + \textit{error}_{ikt}, \qquad (1) \end{aligned}$$

where the dependent variable, *Loan Feature*$_{ikt}$, refers to one of the following features of a loan contract for a borrower *i*'s facility *k* in year *t*: (i) *Log AIS*, (ii) *DSecu*, (iii) *DFinCov*, and (iv) *DGenCov*.

The variable *Log AIS* is used as a proxy for the interest cost of borrowing and is measured by the natural log of the drawn-all-in spread (plus the upfront fee and annual fee, if any) in basis points in excess of the benchmark rate, that is, the London Interbank Borrowing Rate (LIBOR). The variable *DSecu* is an indicator variable that equals one if the loan is secured with collateral and zero otherwise. The variable *DFinCov* is an indicator variable that equals one if the loan includes any financial covenant and zero otherwise. The variable

[9] Feng et al. (2009) have conducted several tests to show the construct validity of *NSPE*.

DGenCov is an indicator variable that equals one if the loan includes any general (non-financial) restrictive covenant, such as dividend restrictions and/or investment restrictions, and zero otherwise. When *Log AIS* is the dependent variable, we estimate Eq. (1) using ordinary least squares (OLS) regression; when *DSecu*, *DFinCov*, or *DGenCov* is the dependent variable, we estimate Eq. (1) by applying probit regression procedures.[10]

The test variable *Log NSPE* is the natural log of one plus the number of SPEs for each firm–year.[11] We merge bank loan data with *Log NSPE* and financial statement data for the fiscal year before loans are initiated. The procedure ensures that our test variable, *Log NSPE*, reflects an observable result of SPE use. Our hypotheses H1 and H2 translate into a positive coefficient on *Log NSPE* (i.e., $\alpha_1 > 0$) when the dependent variable in Eq. (1) is the loan spread (*Log AIS*), the indicator of collateral requirement (*DSecu*), or the indicators of financial and general loan covenants (*DFinCov* and *DGenCov*, respectively). This is because SPEs are related to earnings management and other obfuscations in financial reporting and thus increase the borrower's information risk or deteriorate its credit quality.

Following other studies in the loan contracting literature (e.g., Bharath et al. 2008; Graham et al. 2008; Kim et al. 2011a, 2011b; Lin et al. 2011), we include in Eq. (1) a set of loan-level control variables: *Log Maturity, Log Loan Size, Log NLenders, Performance*

---

[10] We also consider the joint determination of interest rates, collateral requirements, and covenant restrictions and re-estimate the effect of SPE use on these loan terms following the loan contracting literature (Dennis, Nandy, and Sharpe 2000; Ivashina 2009; Bharath et al. 2011). First, prior studies suggest that non-price terms are normally determined before setting the loan interest rate in the loan syndication process. We thus assume that loan spread is affected by the inclusion of collateral and covenants and estimate the effect of SPE use on the loan rate, using an instrumental variable approach, and find similar results to those reported in the paper. Second, since *DSecu* and *DFinCov* (*DGenCov*) are two correlated binary variables, we re-examine the effect of SPE use on collateral requirements and covenant restrictions by estimating a bivariate probit model and find similar results to those reported in the paper. Lastly, to check further on the joint determination of loan terms, we also estimate a system of equations with the loan spread, *DSecu*, *DFinCov*, and *DGenCov* as dependent variables, using the seemingly unrelated regression procedure. The unreported results for this procedure are qualitatively identical to those reported in the paper.

[11] Another possible measure of SPE use is the percentage of SPEs among a firm's reported subsidiaries. However, we argue that it is the existence, not the percentage, of SPEs that facilitates managerial opportunism. Nevertheless, we find qualitatively similar results using the percentage measure.

Pricing, and *Term Loan*. The variable *Log Maturity* is the natural log of loan maturity in months and *Log Loan Size* is measured by the natural log of the dollar amount of each loan facility. Previous studies (e.g., Graham et al. 2008) show that lenders charge lower loan rates for shorter-maturity loans and larger loan facilities. The variable *Log NLenders* is the natural log of the number of lenders in a loan deal and *Performance Pricing* is an indicator variable that equals one for loans with performance pricing provisions and zero otherwise. We expect loan contracts involving larger numbers of lenders and performance pricing provisions to have lower interest rates. To control for potential differences in loan terms between transaction-based term loans and other types of non-term loans that are more relationship based, we include in the model an indicator variable, *Term Loan*, that equals one if the loan facility is a term loan and zero otherwise. Since collateral requirements and covenant restrictions are imposed at the deal level rather than at the facility level, we replace *Log Loan Size* with *Loan Concentration*, which is the dollar amount of the loan deal divided by the borrower's total liabilities (Bharath et al. 2011), with *DSecu*, *DFinCov*, or *DGenCov* used as the dependent variable.

We also control for a set of borrower-specific (sponsor-specific) variables that are known to affect credit quality and thus loan contracting terms: *Size*, *Leverage*, *MB*, *Profitability*, *Funds*, *Tangibility*, *Log IntCov*, *O-Score*, *AbsAccr*, and *Prior*. The variables *Size* and *Leverage* are measured by the natural log of total assets and the ratio of total debt to total assets, respectively. We expect *Size* (*Leverage*) to be positively (negatively) related to credit quality. The variable *MB* is measured by the market value of equity plus the book value of debt divided by the book value of total assets. To the extent that it proxies for a borrower's growth potential, *MB* is likely to be positively associated with credit quality.

However, growing firms often face higher risk. In such a case, *MB* is likely to be inversely associated with credit quality (Billett, King, and Mauer 2007). The variable *Profitability* refers to earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets and *Tangibility* is the ratio of property, plant, and equipment (PP&E) to total assets. The variable *Funds* is a proxy for the supply of internal funds, which is measured by the sum of cash flow from operating activities and cash flow from investing activities divided by average total assets. The variable *Log IntCov* is the natural log of one plus the coverage ratio, that is, the ratio of operating income after depreciation (before interest) to interest expenses. We expect *Profitability, Funds, Tangibility,* and *Log IntCov* to be positively associated with credit quality. The variable *O-Score* is Ohlson's (1980) O-score, a proxy for the borrower's default risk. The term *AbsAccr* is the absolute value of abnormal accruals obtained from the modified Jones model (Dechow et al. 1995). We predict that *AbsAccr*, which is an inverse measure of accounting quality (Bharath et al. 2008), is positively associated with the borrower's information risk. The term *Prior* is an indicator variable that equals one if the borrower has prior loan relationships with at least one of the lead banks of a loan syndicate for the current loan deal in the past five years and zero otherwise. We expect *Prior* to be negatively associated with the loan spread and the likelihood of loans being subject to collateral requirements and restrictive covenants (Bharath et al. 2011).

In addition, we include two economy-wide variables, *Term Spread* and *Credit Spread*, to control for the potential effects of macroeconomic conditions on loan contract terms. The variable *Term Spread* is the difference in yield between 10- and two-year U.S. Treasury bonds, while *Credit Spread* is the difference in yield between BAA- and AAA-rated corporate bonds. Finally, we include *Loan Purpose Indicators* to control for potential differences in the price and non-price terms of loan contracts associated with different loan purposes.[12] We also include *Year Indicators* and *Industry Indicators* to control for potential differences in SPEs and loan features across years and industries.

For the test of H3, we partition our sample into two subsamples based on the median of borrowers' CEO pay–performance sensitivity, that is, delta risk (Core and Guay 2002; Coles et al. 2006), and estimate Eq. (1) for both subsamples.[13] According to H3, we expect a stronger impact of SPE usage on loan terms for the subsample of higher CEO delta risk. For the test of H4, we partition our sample into two subsamples based on whether the borrower and the lead lender have a prior loan relationship and estimate Eq. (1) for both subsamples. According to H4, we expect a stronger impact of SPE usage on loan terms for the subsample of borrowers that have no prior relationships with their lenders.

4. Sample Selection and Descriptive Statistics

4.1 Sample and Data

Our initial sample consists of all public companies that have bank loan data in the Loan Pricing Corporation (LPC) DealScan database for 1997–2008. The LPC DealScan database contains a variety of historical bank loan data and other financial arrangements collected from SEC filings and other information self-reported by banks. The DealScan loan data are compiled for each transaction or deal. Each deal, which is a loan contract between a borrower and bank(s) on a specific date, can have only one facility or a package of several facilities with different price and non-price terms. We consider each facility a separate

[12] The purposes of loan facilities in DealScan include corporate purposes, debt repayment, working capital, takeover, and acquisition lines. Accordingly, *Loan Purpose Indicators* is a series of indicator variables for loans with these different purposes.

[13] Delta is the change in the dollar value of the CEO's wealth associated with a 1% change in the firm's stock price. We are grateful to Jeffrey L. Coles, Naveen D. Daniel, and Lalitha Naveen for providing the data on CEO delta risk.

observation for our sample, since many loan characteristics and loan spreads vary across facilities. We require that all loan facilities in our sample be senior debts. With regard to the types of loans, our sample includes term loans, revolvers, and 364-day facilities but excludes bridge loans and non–fund-based facilities such as leases and standby letters of credit. We also exclude financial companies from our sample. We manually collect the SPE data by searching the annual 10-K reports in Edgar for our sample firms.[14] We obtain borrowers' financial statement data from Compustat. DealScan and Compustat are matched using the linking table originally created by Chava and Roberts (2008).[15] Our final sample consists of 11,088 facility–years. Table 1 presents the sample selection procedure.

[INSERT TABLE 1 HERE]

4.2 Descriptive Statistics and Correlations

Panel A of Table 2 presents descriptive statistics for all loan-specific variables at the facility level. The mean and median of the drawn-all-in spread over the LIBOR (i.e., *AIS*) are around 185 and 175 basis points (bps), respectively, with a standard deviation of about 139 bps, suggesting that *AIS* is reasonably distributed. The mean (median) maturity is about 47 (57) months, while the mean (median) facility size is $372 million ($150 million). On average, the amount of a loan deal accounts for 34% of a borrower's total liability. Panel A of Table 2 also shows that 54% of the loan facilities in our sample require loans to be secured by collateral, about 74% of them include at least one financial (general) covenant, and 57%

[14] Since our SPE measure is lagged by one period, we use computer algorithm to collect SPE data from 10-K filings during 1996–2007. We choose this period to fully cover the sample period (1997–2004) of Feng et al. (2009) to compare the yearly distributions of SPE firms with those reported in their study. Untabulated results show that the yearly distributions of our SPE data are very similar to those of Feng et al. during the common period. The percentage of firm–years reporting at least one SPE in our test sample, 49.5%, is higher than that in the authors' sample, 41.9%, and the SPE firm–years in our test sample report more SPEs (18.73 for the mean and 4.00 for the median) than those in their sample (11.63 for the mean and three for the median). That is because the public firms covered by LPC DealScan are generally larger than the average firms in Compustat.

[15] We are grateful to Michael Roberts for providing the DealScan–Compustat link file.

have a performance pricing provision. Most of the loan facilities in our sample are syndicated loans that have, on average, nine participating lenders. About 29% of the loan facilities in our sample are term loans, while the others are revolvers or 364-day facilities.

[INSERT TABLE 2 HERE]

Panel B of Table 2 reports descriptive statistics for our measures of SPEs and all borrower-specific (lender-specific) variables used in this study. The mean and median numbers of SPE (*NSPE*) sponsored by the borrowers in our sample are about 10 and zero, respectively, with a large standard deviation of 57.88. This suggests that the distribution of *NSPE* is very right skewed. The natural log transformation of *NSPE* (*Log NSPE*) slightly mitigates the skewness. The variable *Size* is reasonably distributed, with a mean and median of 6.87 and 6.79, respectively, and a standard deviation of 1.81. The mean (median) market-to-book ratio is 1.75 (1.46) and the mean (median) O-score is -6.88 (-6.93). On average, long-term debt, EBITDA, and tangible assets (i.e., PP&E) are about 27%, 15%, and 34% of total assets, respectively. The mean and median ratios of internal cash flows to average total assets (*Funds*) are -1% and 2%, respectively. The variable *Log IntCov* has a mean (median) of 1.82 (1.64) and *AbsAccr*, a proxy for accounting quality, has a mean (median) of 0.12 (0.05). About 46% of borrowers in our sample have prior lending relationships with the same lead banks for their current loans.

Table 3 reports Pearson correlation coefficients among selected loan- and borrower-specific variables. Inconsistent with our predictions, we find in Table 3 that *Log NSPE* is significantly and negatively correlated with *Log AIS* (-0.11), *DSecu* (-0.10), *DFinCov* (-0.05), and *DGenCov* (-0.03), suggesting that SPE use is associated with more favorable loan contracting terms. We also find that *Log NSPE* has a strong correlation with *Size* (0.43), while *Size* has significantly negative correlations with *Log AIS* (-0.54), *DSecu* (-0.42), *DFinCov* (-0.24), and *DGenCov* (-0.14). In addition, *Size* is highly correlated with *Log Loan Size* (0.81) and *Log NLenders* (0.60). Thus, our conjecture is that the correlations between SPE use and favorable loan terms are driven by firm size effect. Table 3 shows that SPE use is positively correlated with leverage and asset tangibility, while it is negatively correlated with the market-to-book ratio, profitability, interest coverage, and the O-score.

Among loan contracting terms, *Log AIS* is positively correlated with *DSecu*, *DFinCov*, *DGenCov*, and *Log Maturity*, while it is negatively correlated with *Log Loan Size* and *Performance Pricing*. The variable *DSecu* is positively correlated with both *DFinCov* and *DGenCov* and these two covenant indicators are highly and positively correlated with each other. These correlations are consistent with those reported in the prior loan literature.

[INSERT TABLE 3 HERE]

5. Empirical Results

5.1 Tests of H1 and H2

Table 4 reports the estimated results for Eq. (1). All reported *t*-statistics (*z*-statistics) are based on standard errors corrected for heteroscedasticity and two-dimensional (firm and year) clustering. As shown in column (1), we find that the coefficient on *Log NSPE* is positive and statistically significant at less than the 1% level (coefficient = 0.039, *t*-value = 3.84). This finding is consistent with H1, suggesting that the number of SPEs reported in a company’s 10-K is positively associated with loan interest rates. Stated another way, the above finding is consistent with the view that banks and other private lenders tend to charge higher interest rates for loans made to firms that use SPEs because such firms are perceived as having higher default risk and/or information risk.

The effect of SPE use on loan interest rate is economically significant as well. The magnitude of the coefficient on *Log NSPE* (0.039) suggests that a move from no SPEs (the first quartile of *NSPE* in our sample) to four SPEs (the third quartile of *NSPE* in our sample) leads to a 6.5% increase in *AIS*, with all other *AIS* determinants unchanged.[16] Suppose that a firm without SPEs takes out a loan of $372 million for 47 months at the all-in spread of 185 bps (i.e., an average loan facility in our sample, as shown in Panel A of Table 2). Our results imply that the all-in spread of a loan with the same features borrowed by a firm with four SPEs is 197 bps, that is, 12 bps higher than that of the loan to a borrower without SPEs. In other words, on average, a borrower with four SPEs has to pay annually $0.45 million ($372 million × 12 bps) more interest expense for about four years than a borrower without SPEs.

[INSERT TABLE 4 HERE]

In column (2), the coefficient on *Log NSPE* is also positive and statistically significant at less than the 1% level (coefficient = 0.062, *t*-value = 3.47), suggesting that SPE use increases the likelihood of loans being secured by collaterals. In columns (3) and (4), we find that the coefficients on *Log NSPE* are both positive and statistically significant at less than the 1% level (coefficient = 0.096, *t*-value = 4.74 and coefficient = 0.063, *t*-value = 2.79, respectively). This finding suggests that SPE use is positively associated with the likelihood that lenders impose financial covenants and general covenants in the loan contracts to protect themselves from the SPE sponsor's default risk and/or information risk. In terms of economic significance, the results suggest that when *NSPE* increases from zero to four, the probability of its loans being secured by collaterals increases by 2.7% and the probabilities of its loans being subject to financial and general covenants increase by 2.9% and 1.8%, respectively. As

[16] The calculations are as follows: $Log\ AIS_{\text{NSPE=4}} - Log\ AIS_{\text{NSPE=0}} = 0.039 \times [\ln 5 - \ln 1] = 0.0628$. Thus, $AIS_{\text{NSPE=4}} \div AIS_{\text{NSPE=0}} = e^{0.0628} = 1.0648$. The ratio reflects a 6.5% increase in *AIS* when *NSPE* moves from zero to four.

predicted by H2, banks and other private lenders tend to require collateral and use restrictive covenants in loans made to the sponsor firms of SPEs because those firms are likely to have hidden debt financing and more flexibility in earnings management and thus their borrowers are subject to higher default and information risks.

The results regarding our control variables are consistent with those of previous studies on the cross-sectional determinants of price and non-price terms of loan contracts. For brevity, we omit discussions on those control variables.

5.2 Tests of H3 and H4

Panel A of Table 5 reports the estimated results for Eq. (1) for the two subsamples partitioned based on CEO pay–performance sensitivity, measured by delta. The results show that the coefficients on *Log NSPE* are significantly positive only for the high-delta subsample in columns 1, 2, and 4, where *AIS, DSecu* and *DGenCov*, respectively, are used as the dependent variable (coefficient = 0.062, *t*-value = 4.47 for *AIS*; coefficient = 0.090, *t*-value = 2.74 for *DSecu*; coefficient = 0.087, *t*-value = 2.05 for *DGenCov*). In addition, we find that the coefficients on *Log NSPE* are significantly larger for the subsample of high-delta firms than for the subsample of low-delta firms. Since SPE usage is more likely to be associated with misreporting when borrowers have greater CEO pay–performance sensitivity, our results provide some evidence that banks and other private lenders price the information risk associated with SPE usage and also use non-price terms to facilitate the post-contract monitoring of the sponsor firm's credit quality. In addition, our results suggest that banks' superiority in accessing and processing borrowers' private information is not sufficient to overcome the information risk resulted from SPE usage.

[INSERT TABLE 5 HERE]

Panel B of Table 5 reports the estimated results for Eq. (1) for the subsample of loans made to borrowers who have prior lending relationships with the lead lenders and for the subsample of loans made to borrowers who do not. Panel B shows that the coefficients on *Log NSPE* are significantly positive only for loans made to firms with no prior lending relationship, in columns 2 and 4, where *DSecu* and *DGenCov*, respectively, are used as the dependent variable (coefficient = 0.087, *t*-value = 4.22 for *DSecu*; coefficient = 0.103, *t*-value = 3.57 for *DGenCov*). In addition, the coefficients on *Log NSPE* are significantly larger for the subsample with no prior relationship than for the prior-relationship subsample. For financial covenants, although the coefficients on *Log NSPE* are statistically significant for both subsamples, the estimated coefficient is significantly larger for the subsample with no prior relationship than for the prior-relationship subsample. For loan rates, the coefficients are statistically significant for both subsamples and are not statistically different from each other. The stronger impact of SPE usage on non-price terms for the subsample with no prior relationship suggests that the information risk associated with SPE activities does matter in determining loan contracting terms.

Overall, the results of the subsample analyses provide some direct evidence on the impact of SPE use on increasing information risk faced by banks and other private lenders. Dechow et al. (2010) provide evidence that even informed and independent directors do not distinguish between securitization gains and other components of earnings when awarding CEO pay. The evidence shown in this study suggests that banks and other private lenders price the information risk associated with SPEs in the form of higher loan interest rates.

The analyses also help us rule out the possibility that *Log NSPE* only represents off balance sheet liability. If it is indeed no more than off balance sheet liability, we are unlikely to observe significant differences in the impact of SPE usage on loan terms between the two subsamples (high CEO compensation delta versus low CEO compensation delta and prior relationships versus no prior relationships between lenders and borrowers). In particular, we find that *Log NSPE* is not associated with loan interest rates when the borrowers with SPEs have below-median CEO pay–performance sensitivity, suggesting that *Log NSPE* does not simply represent off balance sheet liability.

5.3 Robustness Check

5.3.1 Selection Bias and Endogeneity

Our analyses thus far focus on how borrowers' SPE usage impacts their loan contracting terms. However, it is possible that some confounding factors that contribute to the formation of SPEs also affect the loan contracting terms in the predicted direction. For example, managerial incentives to boost reported earnings may motivate managers to establish SPEs, which in turn causes lenders to impose unfavorable contracting terms on loans to SPE sponsor firms. To address this self-selectivity concern, we include the absolute value of abnormal accruals in Eq. (1) as a control variable.

In this section, we further control for potential self-selection bias and endogeneity associated therewith. More specifically, we use the propensity score matching (PSM) method to match each treatment firm that uses SPEs with each control firm that does not use SPEs.[17] Following Feng et al. (2009), we use the following model to predict firms' decisions to form SPEs:

$$DSPE_{it} = \alpha_0 + \alpha_1 LEV_{it-1} + \alpha_2 R\_INTCOV_{it-1} + \alpha_3 BONUSP_{it-1} + \alpha_4 DEBTISS_{it-1}$$
$$+ \alpha_5 STOCKISS_{it-1} + \alpha_6 RISK_{it-1} + \alpha_7 FUNDS_{it-1} + \alpha_8 CLTD_{it-1}$$

[17] The PSM method has been used to alleviate potential endogeneity concerns and is supported by a stream of recent accounting studies (e.g., Doyle, Ge, and McVay 2007; Armstrong et al. 2010; Larcker and Rusticus 2010; Lawrence, Minutti-Meza, and Zhang 2011; Francis et al. 2012).

$$+ \alpha_9 TDUM_{it-1} + \alpha_{10} SETR_{it-1} + \alpha_{11} INTANGIBLE_{it-1} + \alpha_{12} FOREIGN_{it-1}$$

$$+ \alpha_{13} LMKTCAP_{it-1} + \alpha_{14} INDPERC_{it-1} + (Year\ Indicators_{it}) + error_{it}, \quad (2)$$

where *DSPE* is an indicator that equals one if the firm reports SPEs and zero otherwise.[18] The predictors of *DSPE* include leverage, defined as total debt divided by total assets (*LEV*); the reverse interest coverage ratio, that is, interest expense divided by operating income after depreciation (before interest) (*R_INTCOV*);[19] the bonus percentage, that is, the ratio of the CEO bonus to the sum of salary and bonus (*BONUSP*); the issue of debt, defined as the difference between long-term debt issuance deflated by average total assets (*DEBTISS*); and the issue of stock, defined as the difference between the common and preferred stock sale and purchase deflated by average total assets (*STOCKISS*); stock return volatility, measured by the decile rank score of the standard deviation of daily stock returns for the year (*RISK*); internal cash flows, defined as the sum of operating cash flow and investing cash flow deflated by average total assets (*FUNDS*); the costs of debt renegotiation, defined as long-term debt due within one year divided by total assets (*CLTD*); a tax rate dummy, which is an indicator that takes the value of one if the pretax income is positive and zero otherwise (*TDUM*);[20] the state effective tax rate, defined as the sum of current and deferred state income tax expenses divided by total pretax income (*SETR*); intangible assets, which is measured by intangible assets deflated by total assets (*INTANGIBLE*); foreign income, defined as the ratio of foreign pretax income to total pretax income (*FOREIGN*); the natural log of the sum of the market value of common shares and the book value of preferred stock

[18] For Feng et al. (2009), the dependent variable is the number of SPEs. For the purpose of the PSM test, we use the dummy variable *DSPE* as the dependent variable to run the first-stage probit model.

[19] We use the reverse interest coverage ratio to maintain firm–year observations with zero interest expense. So the predicted sign of the coefficient on *R_INTCOV* should be positive.

[20] Feng et al. (2009) use a simulated marginal tax rate as the predictor of tax benefits. They also suggest using a dummy variable that indicates whether firms need to pay income tax because of positive profits as a replacement.

and liabilities (*LMKTCAP*); the industry SPE percentage, defined as the percentage of firms reporting SPEs within each industry–year, with industries classified according to the Fama–French (1997) 48-industry classification (*INDPERC*); and year indicators.[21]

For all firms in our sample, we first compute the predicted probability (i.e., propensity score) of SPE use, using the estimated coefficients of the probit regression model in Eq. (2). For each treatment firm, we then choose a matched control firm that has the closest predicted probability of SPE use to that of the treatment firm. After applying the above PSM procedure, we obtain a matched sample of 4,318 loan facilities consisting of 2,159 facilities for borrowing firms with SPEs and 2,159 facilities for borrowing firms without SPEs. We first compare the distributions of the control variables in Eq. (1) between the treatment firms with SPEs and the control firms with no SPEs. Though not tabulated for brevity, we do not find significant differences in various firm characteristics between these two samples, suggesting that the PSM matching is effective. We then re-estimate Eq. (1) using this PSM sample. Panel A of Table 6 reports the estimated results of the first-stage probit model for predicting *DSPE*, which are similar to those reported by Feng et al. (2009). Panel B of Table 6 reports the estimated results of Eq. (1) using the PSM sample. As shown in Panel B, the coefficients on *Log NSPE* are all positive and statistically significant at less than the 5% level when *Log AIS*, *DSecu*, or *DFinCov* is the dependent variable, suggesting that our main results are unlikely to be driven by potential endogeneity associated with a firm's voluntary decision to use SPEs.

[INSERT TABLE 6 HERE]

[21] Since, as argued by Feng et al. (2009), the additional data requirement for governance variables reduces the sample size by one-third, we do not include these governance variables in Eq. (2) to maintain our sample size. We obtain similar but slightly weaker results if the governance variables are included in Eq. (2).

5.3.2 Within-Firm Analysis

In this section, we perform additional tests to examine temporal changes in loan contracting terms before and after the launching of SPEs. To do so, we identify the first-time filing date of SPEs in 10-K by each SPE sponsor firm. We then require that the SPE firm have at least one loan facility within the two years before and after its first-time SPE filing via 10-K. We choose the loan facilities initiated around the SPE firms' first-time filing of SPEs because it provides the most powerful setting for investigating the potential effect of SPE use on temporal changes in loan terms. After applying the above selection procedure, we construct a sample of 2,343 loan facilities borrowed by 541 SPE firms over the four-year period surrounding their first-time SPE filing dates. The test variable of this temporal analysis is *AfterSPE*, an indicator variable that equals one if the loan facility is initiated after the borrower files SPEs for the first time and zero if initiated before.

Using this reduced sample, we regress loan terms on *AfterSPE* and a set of control variables. If banks perceive the use of SPEs as a credit-risk increasing factor and, thus, adjust various loan terms accordingly, we expect to observe a significant coefficient on *AfterSPE*. The estimated results are reported in Panel C of Table 6. Columns (1) and (2) show that the estimated coefficient on *AfterSPE* is significantly and positively associated with *Log AIS* and *DSecu*, suggesting that loans issued after borrowers start using SPEs tend to have higher interest rates and are more likely to have collateral requirements, compared with loans issued before the use of SPEs. We find, however, that the coefficients on *AfterSPE* are insignificant when *DFinCov* or *DGenCov* is used as the dependent variable.

5.4 Additional Analyses

5.4.1 Controlling for Borrower Credit Ratings

When credit rating agencies and bond analysts evaluate firm credit risk, they evaluate both on and off balance sheet liabilities (e.g., Moody's 2006; Standard & Poor's 2006; Kraft 2009) and, thus, credit ratings should reflect the evaluation of the off balance sheet liability and default risk of the rated firms. In this section, we include Standard & Poor's long-term issuer credit rating (*Rating*)[22] in Eq. (1) to better control for the default risk and off balance sheet liability of SPE sponsor firms. To some extent, the inclusion of *Rating* allows us to separate the effect of SPE usage on information risk from its effect on default risk. Table 7 presents the estimated results for Eq. (1), with *Rating* included as an additional control variable. Note here that our sample size drops by about a half. Table 7 shows that the coefficient on our measure of SPE usage remains positive and significant at conventional levels, even after controlling default risk proxied by the sponsor firms' credit ratings. This result lends further support to the view that banks and other private lenders perceive SPE usage to be a factor that increases information risk.

[INSERT TABLE 7 HERE]

5.4.2 Effect of SPE Usage on Earnings Restatement and Future Default

As discussed earlier, SPE usage may affect both the default and information risks of sponsor firms. SPE usage facilitates managerial opportunism in financial reporting and reduces the quality of financial reports. As a result, outside capital suppliers are likely to face higher information risk when evaluating the default risk of SPE sponsor firms and, thus, charge higher loan rates and/or impose more stringent non-price terms to make up for bearing the information risk. As for default risk, SPE usage may lower or increase it, depending on

[22] Credit ratings are transformed into a numerical value (*Rating*) ranging from one to 22. A smaller value for *Rating* indicates a better credit rating (e.g., one for AAA and two for AA+).

whether the economic benefits of SPE usage dominate or are dominated by the associated costs. Lemmon et al. (2014) find no evidence of any deterioration in credit quality after the initiation of securitization programs.

To further examine the mechanisms through which SPE usage affects loan contracting, we test whether SPEs are associated with opaque financial reporting represented by accounting restatement and future credit default. Following Dechow et al. (2011), we run a probit regression to estimate the effect of SPE usage on the likelihood of future accounting restatements. Panel A of Table 8 reports the estimated results.[23] As shown in Panel A, we find that the coefficient on SPE usage in the probit regression is positive and highly significant at less than the 1% level. This finding suggests that SPE use is positively associated with the likelihood of future misstatements of financial reports, suggesting that SPE usage increases the opacity of financial reports. This result lends further support to our argument that SPEs are used as a tool for opportunistic earnings management.

[INSERT TABLE 8 HERE]

Second, we examine whether our measure of SPE usage can predict the actual occurrence of credit defaults observed for our sample firms. If SPE usage is only associated with the sponsor's default risk, it should be a significant predictor of actual defaults or bankruptcies. Following the recent bankruptcy prediction literature (Chava and Jarrow 2004; Chava, Livdan, and Purnanandam 2009), we estimate the Cox (1972) proportional hazard model to assess the predictive power of SPE usage with respect to actual defaults for the sponsor firms in our sample. The data on actual default events are obtained from Moody's Corporate Default Risk Service. Panel B of Table 8 reports the estimated results for the

[23] We use Accounting and Auditing Enforcement Releases issued by the SEC against the company to identify firms that misstate their earnings.

hazard model of default prediction. We find that the coefficient on *Log NSPE* is insignificant. The finding suggests that SPE use does not have the ability to predict the occurrence of actual defaults or default risk.

In short, the use of SPEs can predict the likelihood of financial restatement in the future, but it does not have the predictive ability with respect to actual defaults. The results reported in both Panels A and B of Table 8, taken together, suggest that the use of SPEs is associated more closely with information risk of the sponsor firm rather than its default risk.

5.4.3 Asset Securitization

Following Feng et al. (2009), our main measure of SPE usage is a count of the limited partnerships, limited liability partnerships, limited liability companies, and trusts included in the list of subsidiaries and affiliates reported in Exhibit 21 of 10Ks. The merit of this measure is that it incorporates all types of SPEs. However, it is also possible that this measure does not capture the real underlying SPE activities carried out by the firms. In this section, we examine whether and how the existence of a specific and common type of SPE, that is, asset securitization, affects loan contracting, using the data made available by Lemmon et al. (2014) from the sample period 1996–2009.[24]

Specifically, in Eq. (1), we replace our SPE measure (*Log NSPE*) with *ABSDUM*, that is, an indicator variable that equals one if the firm reports an on-going asset securitization program in its 10K and zero otherwise. At the same time, we adjust the leverage ratio by adding the amount of SPE borrowings disclosed in the 10K to both the numerator and denominator if the SPE is unconsolidated,[25] essentially treating the securitization as

---

[24] We thank the authors Lemmon, Liu, Mao, and Nini for providing the data on their website.
[25] By including a consolidation dummy in Eq. (1), we also find that the negative consequence of securitization on loan interest rates and collateral requirements is mitigated if the SPE is consolidated. The consolidation dummy takes the value of one if the borrower mentions in the 10K that the SPE is consolidated and zero

collateralized borrowings instead of sales of receivables.[26] To address potential endogeneity with respect to asset securitization, in the first stage we run a probit model to estimate the propensity score of a firm's decision to initiate a securitization program, using the same set of predictor variables as Lemmon et al. (2014). Then we match each treatment firm (with securitization) with the control firm (without securitization) that has the closest propensity score.

Panel A of Table 9 reports the estimated results for the first-stage probit regression. Panel A shows that similar to the results reported in Lemmon et al. (2014), the likelihood of a firm engaging in asset securitization is higher for larger firms, firms with larger account receivables (*AR*) or higher leverage (*Leverage*), and firms with BB+ credit rating or below (*BB*). Panels B and C present the estimated results for Eq. (1), using the full sample and the PSM sample, respectively. As shown in Panel B, the full-sample results reveal that asset securitization is positively associated with loan spread, collateral requirements, and financial covenant restrictions at less than the 1% level. The results using the PSM sample in Panel C show essentially the same results as those reported in Panel B, which buttresses our full-sample results.

[INSERT TABLE 9 HERE]

6. Conclusions

In this study, we examine the effect of SPE usage on various terms of loan contracts. Often SPEs are established to serve the economic purposes of isolating financial risk, accessing segmented capital markets, reducing finance costs, and maximizing tax benefits.

---

otherwise. However, such information is not very reliable. Out of 523 firms that reported securitization in their 10Ks, only 34 of them mentioned that the SPE was consolidated. In addition, due to accounting loopholes, firms can easily avoid consolidating their SPEs, making the consolidation decision a self-selected choice.

[26] Prior studies suggest that off-balance-sheet debt related to securitizations is treated as secured borrowings by equity market participants (Landsman, Peasnell, and Shakespeare 2008; Niu and Richardson 2010).

Since the collapse of Enron, the public has begun to pay close attention to the dark side of SPEs. The Enron investigation revealed that SPEs were one of the main tools used by Enron executives to hide losses and unfavorable performance. Nevertheless, there is a lack of general evidence on the broader issue of whether and how SPE use is perceived by market participants when contracting with the sponsor firms that use SPEs. A recent study by Lemmon et al. (2014) shows that the equity market reacts positively to the initiation of asset securitization and the bond market does not generate a significant reaction to such events. Their findings suggest that asset securitization provides a beneficial form of external financing to equity holders without hurting debt holders. Our study aims to provide large-sample, systematic evidence on the effect of SPEs on both the price and non-price terms of bank loan contracts. Specifically, our study focuses on examining the consequences of information risk associated with SPE usage, which is not considered by Lemmon et al. (2014).

We empirically show that banks and other private lenders perceive SPEs as a significant factor that increases credit risk. Our results show that firms with SPEs tend to pay higher loan interest rates and are more likely to have their loans secured by collateral or subject to restrictive covenants. In an attempt to show some direct evidence on the impact of SPE usage on information risk, we further examine the relation between SPE usage and loan contracting terms conditional on CEO pay–performance sensitivity and the existence of a prior lending relationship. We find that the negative effect of SPE usage on bank loan terms is more pronounced for SPE sponsor firms with higher CEO pay–performance sensitivity and no prior lending relationship with the lenders. This finding suggests that SPE usage is associated with higher information risk, which in turn leads to higher loan interest rates and unfavorable non-price terms.

One of the limitations of our study lies in the challenge of distinguishing the effect of SPE usage on default risk from that on information risk. In an effort to provide direct evidence on SPE usage as an information risk-increasing factor, besides the subsample analyses, we also include the credit rating variable as an additional control variable in the regressions. Moreover, we show evidence that SPE usage is linked to future accounting restatements, but not future credit default. We admit, however, that none of these tests can perfectly separate the effect of SPE use on information risk from that on default risk. The other limitation is that, to better evaluate the economic benefits and costs of using SPEs, we should also examine the financing costs of the entity in its totality, that is, the sponsor plus the SPE. However, due to data unavailability, we can only show that SPE usage increases loan contracting costs for the sponsor firms.

References

Armstrong, C. S., A. D. Jagolinzer, and D. F. Larcker. 2010. Chief executive officer equity incentives and accounting irregularities. *Journal of Accounting Research* 48 (2): 225–271.

Ayotte, K, and S. Gaon. 2011. Asset-Backed Securities: Costs and Benefits of “Bankruptcy Remoteness.” *The Review of financial studies* 24 (4):1299-1335.

Barth, M. E., Ormazabal, G., and Taylor, D. J. 2011. Asset securitizations and credit risk. *The Accounting Review*, 87(2), 423-448.

Basmann, R. L. 1960. On finite sample distributions of generalized classical linear identifiability test statistics. *Journal of the American Statistical Association* 55 (292): 650–659.

Beatty, A., P. G. Berger, and J. Magliolo. 1995. Motives for forming research and development financing organizations. *Journal of Accounting and Economics* 19 (2–3): 411–442.

Beatty, A., K. Ramesh, and J. P. Weber. 2002. The importance of accounting changes in debt contracts: The cost of flexibility in covenant calculations. *Journal of Accounting and Economics* 33 (2): 205–227.

Berger, A. N., and G. F. Udell. 1990. Collateral, loan quality, and bank risk. *Journal of Monetary Economics* 25 (1): 21–42.

Bergstresser, D., and Philippon, T., 2006. CEO incentives and earnings management. Journal of Financial Economics 80, 511–529.

Bharath, S. T., S. Dahiya, A. Saunders, and A. Srinivasan. 2011. Lending relationships and loan contract terms. *Review of Financial Studies* 24 (4): 1141–1203.

Bharath, S. T., J. Sunder, and S. V. Sunder. 2008. Accounting quality and debt contracting. *The Accounting Review* 83 (1): 1–28.

Billett, M. T., T.-S. D. King, and D. C. Mauer. 2007. Growth opportunities and the choice of leverage, debt maturity, and covenants. *Journal of Finance* 62(2): 697–730.

Bloomberg Finance. 2014. Bloomberg 2013 global syndicated loan league tables. http://www.bloomberg.com/professional/content/uploads/sites/2/2014/01/Syndicated-Loans-2013.pdf

Bradley, M., and M. R. Roberts. 2004. The structure and pricing of corporate debt covenants. Working Paper, Duke University.

Burns, N., and S. Kedia. 2006. The impact of performance-based compensation on misreporting. *Journal of Financial Economics* 79 (1): 35–67.
Chava, S., and R. Jarrow. 2004. Bankruptcy prediction with industry effects. *Review of Finance* 8 (4): 537–569.

Chava, S., D. Livdan, and A. Purnanandam. 2009. Do shareholder rights affect the cost of bank loans? *Review of Financial Studies* 22 (8): 2973–3004.

Chava, S., and M. R. Roberts. 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* 63 (5):2085-2121.

Chen, W., C. Liu, and S. Ryan, 2008. Characteristics of securitization that determine issuers' retention of the risk of the securitized assets. *The Accounting Review* 83 (5): 1181–1215.

Cheng, M., D. Dhaliwal, and M. Neamtiu. 2011. Asset securitization, securitization resource, and information uncertainty. *The Accounting Review* 86 (2): 541–568.

Coles, J. L., N. D. Daniel, and L. Naveen. 2006. Managerial incentives and risk-taking. *Journal of Financial Economics* 79 (2): 431-468.

Core, J., and W. Guay. 2002. Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting Research* 40(3): 613-630.

Costello, A. M., and R. Wittenberg-Moerman. 2011. The impact of financial reporting quality on debt contracting: Evidence from internal control weakness reports. *Journal of Accounting Research* 49 (1): 97–136.

Cox, D. R. 1972. Regression models and life-tables. *Journal of the Royal Statistical Society*, Series B (Methodological) 34 (2): 187–220.

Downing, C., D. Jaffee, and N. Wallace. 2009. Is the market for mortgage-backed securities a market for lemons?. *Review of Financial Studies 22*(7): 2457-2494.

Dechow, P. M., W. Ge, C. Larson, and R. Sloan. 2011. Predicting material accounting misstatements. Contemporary Accounting Research 28: 17–82

Dechow, P. M., L. A. Myers, and, C. Shakespeare.2010. Fair value accounting and gains from asset securitizations: A convenient earnings management tool with compensation side-benefits. *Journal of Accounting and Economics* 49 (1–2): 2–25.

Dechow, P. M., and C. Shakespeare. 2009. Do managers time securitization transactions to obtain accounting benefits? *The Accounting Review* 84 (1): 99–132.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70(2): 193–225.

Demiroglu, C., and C. M. James. 2010. The information content of bank loan covenants. *Review of Financial Studies* 23 (10): 3700–3737.

Dennis, S., D. Nandy, and Sharpe, I.G., 2000. The determinants of contract terms in bank revolving credit agreements. *Journal of Financial and Quantitative Analysis* 35(1): 87–110.

Dou, Y., Liu, Y., Richardson, G., and Vyas, D., 2014. The risk-relevance of securitizations during the recent financial crisis. *Review of Accounting Studies* 19 (2): 839–876.

Doyle, J., W. Ge, and S. McVay. 2007. Accruals quality and internal control over financial reporting. *The Accounting Review* 82 (5): 1141–1170.

Duffie, D., and D. Lando. 2001. Term structures of credit spreads with incomplete accounting information. *Econometrica* 69 (3): 633–664.

Easley, D., and M. O'Hara. 2004. Information and the cost of capital. *Journal of Finance* 59 (4): 1553–1583.

Fama, E., and K. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2): 153–193.

Feng, M., J. D. Gramlich, and, S. Gupta. 2009. Special purpose vehicles: Empirical evidence on determinants and earnings management. *The Accounting Review* 84 (6): 1833–1876.

Financial Accounting Standards Board. 1990. Statement of Nonsubstantive Lessors, Residual Value Guarantees, and Other Provisions in Leasing Transactions. Emerging Issues Task Force 90–15. Norwalk, CT: Financial Accounting Standards Board.

Financial Accounting Standards Board. 2009a. Statement of Financial Accounting Standards No. 166: Accounting for Transfers of Financial Assets – an amendment of FASB Statement NO. 140. Norwalk, CT: Financial Accounting Standards Board.

Financial Accounting Standards Board. 2009b. Statement of Financial Accounting Standards No. 167: Amendments to FASB Interpretation No. 46(R). Norwalk, CT: Financial Accounting Standards Board.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39 (2): 295–327.

Francis, J. R., C. S. Lennox, and Z. Wang. 2012. Selection models in accounting research. *The Accounting Review* 87 (2): 589–616.

Graham, J. R., S. Li, and J. Qiu. 2008. Corporate misreporting and bank loan contracting. *Journal of Financial Economics* 89 (1): 44–61.

Gupta, S., and L. F. Mills. 2002. Corporate multistate tax planning: Benefits of multiple jurisdictions. *Journal of Accounting and Economics* 33 (1): 117–139.

Hartgraves, A., and G. Benston. 2002. The evolving accounting standards for special purpose entities and consolidations. *Accounting Horizons* 16 (3): 245–258.

Ivashina, V. 2009. Asymmetric information effects on loan spreads. *Journal of Financial Economics* 92 (2): 300–319.

Jimenez, G., V. Salas, and J. Saurina. 2006. Determinants of collateral. *Journal of Financial Economics* 81 (2): 255–281.

Jones, J. D., W. W. Lang, and P. J. Nigro. 2005. Agent bank behavior in bank loan syndications. *Journal of Financial Research* 28 (3): 385–402.

Keys, B. J., Mukherjee, T., Seru, A., and Vig, V. (2010). Did securitization lead to lax screening? Evidence from subprime loans. *The Quarterly Journal of Economics* 125 (1): 307-362.

Kim, J.-B., Li, Y., and Zhang, L., 2011a. CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics* 101(3): 713–730.

Kim, J.-B., B. Y. Song, and L. Zhang. 2011b. Internal control weakness and bank loan contracting: evidence from SOX Section 404 disclosures. *The Accounting Review* 86 (4): 1157–1188.

Kim, J.-B., J. Tsui, and C. H. Yi. 2011c. The voluntary adoption of international financial reporting standards and loan contracting around the world. *Review of Accounting Studies* 16 (4): 779–811.

Kraft, P. 2009. Rating agency adjustments to GAAP financial statements and their effect on ratings and bond yields. Working paper, New York University.

Lambert, R., C. Leuz, and R. Verrecchia. 2007. Accounting information, disclosure, and cost of capital. *Journal of Accounting Research* 45 (2): 385–420.

Landsman, W., K. Peasnell, and C. Shakespeare. 2008. Are asset securitizations sales or loans? *The Accounting Review* 83 (5): 1251–1272.

Larcker, D. F., and T. O. Rusticus. 2010. On the use of instrumental variables in accounting research. *Journal of Accounting and Economics* 49 (3): 186–205.

Lawrence, A., M. Minutti-Meza, and P. Zhang. 2011. Can Big 4 versus non-Big 4 differences in audit quality proxies be attributed to client characteristics? *The Accounting Review* 86 (1): 259–286.

Lemmon, M., L. X. Liu, M. Q. Mao, and G. Nini. 2014. Securitization and capital structure in nonfinancial Firms: An empirical investigation. *Journal of Finance* 69(4): 1787–1825.

Lin, C., Y. Ma, P. Malatesta, and Y. Xuan. 2011. Ownership structure and the cost of corporate borrowing. *Journal of Financial Economics* 100 (1): 1–23.

Mian, A., and Sufi, A., 2009. The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics* 124 (4): 1449-1496.

Moody's. 2006. Moody's Approach to Global Standard Adjustments in the Analysis of Financial Statements for Non-Financial Corporations—Part I. New York, NY: Moody's.

Nadauld, T. D. and M. S. Weisbach. 2012. Did securitization affect the cost of corporate debt? *Journal of financial economics* 105 (2): 332-352.

Niu, F. F., and G. D. Richardson. 2006. Are Securitizations in Substance Sales or Secured Borrowings? Capital-Market Evidence. *Contemporary Accounting Research 23* (4): 1105-1133.

Ohlson, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 18 (1): 109–131.

Piskorski, T., A. Seru, and V. Vig. 2010. Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis. *Journal of Financial Economics* 97 (3): 369-397.

Powers, W. 2002. Report of investigation by the special investigative committee of the board of directors of Enron Corp. (February 1). Available at http://news.findlaw.com/wp/docs/enron/specinv020102rpt1.pdf.

Standard & Poor's. 2006. Corporate Ratings Criteria. New York, NY: S&P.

Rajan, R. G., and A. Winston. 1995. Covenants and collateral as incentives to monitor. *Journal of Finance* 50 (4): 1113–1146.

Soroosh, J., and J. T. Ciesielski, 2004. Accounting for special purpose entities revised: FASB Interpretation 46(R). *The CPA Journal* 74: 30–37.

Shevlin, T. 1987. Taxes and off-balance-sheet financing: Research and development limited partnerships. The Accounting Review 62: 480–509.

U.S. Securities and Exchange Commission. 2005. Report and recommendations pursuant to Section 401(c) of the Sarbanes–Oxley Act of 2002 on arrangements with off-balance sheet implications, special purpose entities, and transparency of filings by issuers, June 15. Available at: http://www.sec.gov/news / studies / soxoffbalancerpt.pdf.

Yale, G. 2002. Enron: An Accounting Analysis of How SPEs Were Used to Conceal Debt and Avoid Losses. Florham Park, NJ: Financial Executives Institute (FEI) Research Foundation.

Appendix. Variable Definitions

Test variables	
NSPE	The number of SPEs used by the borrower.
Log NSPE	The natural log of one plus *NSPE*.
AfterSPE	An indicator variable that equals one when the loan facility is initiated after the borrower starts using SPEs and zero otherwise.
Loan-specific variables	
AIS	The drawn-all-in spread charged by the bank over the LIBOR for the drawn portion of the loan facility, obtained from the DealScan database.
Log AIS	The natural log of *AIS*.
Maturity	The maturity of the loan in months.
Log Maturity	The natural log of *Maturity*.
Loan Size	The amount of the loan facility in millions of dollars.
Log Loan Size	The natural log of *Loan Size*.
Loan Concentration	*Deal Size* divided by the sum of *Deal Size* and the borrower's total liabilities.
Deal Size	The dollar amount of the loan deal in millions of dollars.
Log Deal Size	The natural log of *DealSize*.
NLenders	The number of banks in the loan deal.
NDomLenders	The number of domestic banks in the loan syndicate.
NForLenders	The number of foreign banks in the loan syndicate.
Log NLenders	The natural log of *NLenders*.
Performance Pricing	An indicator variable that equals one if the loan contract includes performance pricing provisions and zero otherwise.
Term Loan	An indicator variable that equals one if the loan facility is a term loan and zero otherwise
DSecu	An indicator variable that equals one if the loan is secured with collateral and zero otherwise.
DFinCov	An indicator variable that equals one if the loan contract includes any financial covenants and zero otherwise.
DGenCov	An indicator variable that equals one if the loan contract includes any general covenants and zero otherwise.
Top Lead	An indicator variable that equals one if at least one of the lead arrangers for the loan was a top 25 U.S. lead arranger (in terms of loan volume) in the year of loan initiation, based on loan data from DealScan, and zero otherwise.
Loan Purpose Indicators	A series of indicator variables for the purposes of loan facilities in DealScan, including corporate purposes, debt repayment, working capital, CP backup, takeover, acquisition lines, and leverage buyout offers.
Log AvgAIS	The natural log of the average *AIS* for loans initiated over the past six months.
Borrower-specific variables	
Size	Firm size, which is the natural log of total assets in millions of dollars.
Leverage	Leverage ratio, defined as long-term debt divided by total assets.

MB	Market-to-book ratio, measured as the market value of equity plus the book value of debt divided by total assets.
Profitability	EBITDA divided by average total assets.
Funds	Supply of internal funds, which is measured by the sum of cash flows from operating activities and cash flows from investing activities divided by average total assets.
Tangibility	Net PP&E divided by total assets.
IntCov	Interest coverage ratio, which is measured by the ratio of operating income after depreciation (before interest) to interest expenses.
Log IntCov	The natural log of one plus *IntCov*.
O-Score	Ohlson's (1980) O-score, where a larger *O-Score* implies a higher default risk: O-score = –1.32 – 0.407 × log(total assets) + 6.03 × (total liabilities/total assets) – 1.43 × (working capital/total assets) + 0.076 × (current liabilities/current assets) – 1.72 × (1 if total liabilities > total assets, 0 otherwise) – 2.37 × (net income/total assets) – 1.83 × (operating income before depreciation/total liabilities) + 0.285 × (1 if net income is negative for the last two years, 0 otherwise) – 0.521 × ((net income$_t$ – net income$_{t-1}$)/ (|net income$_t$| + |net income$_{t-1}$|)).
Prior	An indicator variable that equals one if the borrower had a prior loan relationship with at least one of the lead banks for the current loan deal in the past five years and zero otherwise.
AbsAccr	The absolute value of abnormal accruals obtained from the modified Jones model (Dechow et al. 1995), considering accounting conservatism (Ball and Shivakumar 2006).
Rating	Numerical transformation from Standard and Poor's domestic long term issuer credit rating, ranging from one to 22. A smaller value of *Rating* indicates a better credit rating.
Macroeconomic variables	
Term Spread	Difference in the yield between 10- and two-year U.S. Treasury bonds measured one month before the loan becomes active, obtained from the Federal Reserve Board of Governors.
Credit Spread	Difference in yield between BAA- and AAA-rated corporate bonds measured one month before the loan becomes active, obtained from the Federal Reserve Board of Governors.

Table 1: Sample Selection

	Firms	Loan facilities
Loans to public companies available in DealScan from 1997 to 2008	6,292	32,108
Less:		
Loans borrowed by companies without an identifiable Exhibit 21 in their 10K filings	(1,593)	(10,687)
Loans borrowed by companies in the financial industry	(567)	(2,851)
Non-senior debts, bridge loans, bonds, letters of credit, and other non–fund-based facilities	(82)	(1,520)
Observations missing necessary data items for tests	(1,384)	(5,962)
Total observations	2,666	11,088

Notes: This table reports the sample selection procedure for our data during the period 1997–2008.

Table 2: Descriptive Statistics
Panel A: Loan Characteristics

Variables	Mean	1st quartile	Median	3rd quartile	Std. deviation
AIS (bps)	184.980	75.000	175.000	250.000	139.152
Maturity (months)	46.873	31.000	57.000	60.000	23.057
Loan Size (millions $)	371.965	50.000	150.000	390.000	840.927
DSecu	0.542	0.000	1.000	1.000	0.498
Loan Concentration	0.340	0.163	0.322	0.478	0.210
DFinCov	0.735	0.000	1.000	1.000	0.441
DGenCov	0.740	0.000	1.000	1.000	0.439
Performance Pricing	0.569	0.000	1.000	1.000	0.495
NLenders	9.506	3.000	7.000	13.000	10.117
Term Loan	0.285	0.000	0.000	1.000	0.451

Panel B: Borrowing Firm Characteristics

Variables	Mean	1st quartile	Median	3rd quartile	Std. deviation
NSPE	10.608	0.000	0.000	4.000	57.876
Log NSPE	0.976	0.000	0.000	1.609	1.300
Size	6.867	5.613	6.794	8.016	1.810
Leverage	0.270	0.109	0.240	0.382	0.220
MB	1.754	1.152	1.457	1.980	1.132
Profitability	0.153	0.099	0.139	0.191	0.082
Funds	-0.012	-0.053	0.017	0.070	0.164
Tangibility	0.335	0.144	0.277	0.493	0.235
Log IntCov	1.819	1.086	1.638	2.417	1.274
O-Score	-6.882	-8.070	-6.932	-5.850	2.134
AbsAccr	0.122	0.020	0.051	0.117	1.962
Prior	0.463	0.000	0.000	1.000	0.499

Notes: This table presents the descriptive statistics of the major variables. The sample period is from 1997 to 2008 and the sample consists of 11,088 observations of loan facilities. All variables are as defined in the Appendix.

Table 3: Pearson Correlation Matrix

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Log NSPE	A	1.00																		
Log AIS	B	**-0.11**	1.00																	
DSecu	C	**-0.10**	**0.59**	1.00																
DFinCov	D	**-0.05**	**0.20**	**0.38**	1.00															
DGenCov	E	**-0.03**	**0.17**	**0.38**	**0.82**	1.00														
Log Maturity	F	**0.04**	**0.19**	**0.24**	**0.16**	**0.18**	1.00													
Log Loan Size	G	**0.37**	**-0.49**	**-0.33**	**-0.13**	**-0.03**	**0.06**	1.00												
Log NLenders	H	**0.26**	**-0.31**	**-0.20**	**0.05**	**0.13**	**0.14**	**0.66**	1.00											
Performance Pricing	I	**-0.02**	**-0.08**	**0.12**	**0.56**	**0.60**	**0.19**	**0.11**	**0.22**	1.00										
Size	J	**0.43**	**-0.54**	**-0.42**	**-0.24**	**-0.14**	**-0.10**	**0.81**	**0.60**	**-0.02**	1									
Leverage	K	**0.09**	**0.23**	**0.14**	0.00	**0.03**	**0.12**	**0.09**	**0.14**	**-0.04**	**0.09**	1								
MB	L	**-0.04**	**-0.22**	**-0.10**	**-0.02**	**-0.02**	**-0.03**	**0.05**	0.00	0.00	-0.01	**-0.11**	1							
Profitability	M	**-0.07**	**-0.23**	**-0.10**	**0.03**	**0.02**	**0.03**	**0.06**	**0.04**	**0.08**	**-0.07**	**-0.10**	**0.53**	1						
Funds	N	0.01	**-0.15**	**-0.12**	**-0.03**	**-0.03**	**-0.04**	**0.03**	0.00	**-0.03**	**0.08**	**-0.15**	**0.08**	0.14	1					
Tangibility	O	**0.06**	**-0.05**	**-0.07**	**-0.04**	**-0.03**	**-0.04**	**0.15**	**0.09**	-0.01	**0.18**	**0.23**	**-0.12**	**0.06**	**-0.06**	1				
Log IntCov	P	**-0.03**	**-0.35**	**-0.21**	0.01	-0.00	-0.01	**0.06**	0.01	**0.10**	**-0.02**	**-0.52**	**0.40**	**0.58**	**0.13**	**-0.19**	1			
O-Score	Q	**-0.05**	**0.38**	**0.22**	0.01	0.01	-0.01	**-0.17**	**-0.10**	**-0.12**	**-0.15**	**0.56**	**-0.23**	**-0.36**	**-0.09**	**0.11**	**-0.67**	1		
AbsAccr	R	-0.01	**0.03**	**0.02**	0.01	0.01	0.01	-0.02	-0.00	**-0.02**	-0.01	-0.01	0.00	-0.01	**0.03**	**-0.02**	-0.02	0.02	1	
Prior	S	**0.11**	**-0.16**	**-0.13**	**-0.07**	**-0.05**	**-0.05**	**0.24**	**0.22**	**0.01**	**0.25**	**0.05**	0.00	0.00	**-0.04**	**0.05**	**-0.02**	**-0.02**	-0.01	1.00

Notes: This table reports the Pearson correlation matrix for the major variables used in our empirical tests. The sample period is from 1997 to 2008. All variables are as defined in the Appendix. The correlations in boldface indicate significance at less than the 10% level in a two-tailed test.

Table 4: Number of SPEs and Loan Contracting

VARIABLES	(1) *Log AIS*	(2) *DSecu*	(3) *DFinCov*	(4) *DGenCov*
Log NSPE	0.039***	0.062***	0.096***	0.063***
	(3.84)	(3.47)	(4.74)	(2.79)
Log Maturity	0.111***	0.185***	-0.100**	-0.094
	(5.88)	(4.80)	(-2.09)	(-1.59)
Log Loan Size	-0.054***			
	(-6.39)			
Loan Concentration		1.102***	-0.050	0.466***
		(4.76)	(-0.30)	(2.89)
Log NLenders	0.003	-0.106**	0.214***	0.226***
	(0.20)	(-2.55)	(5.52)	(5.04)
Performance Pricing	-0.056***	0.441***	1.863***	2.043***
	(-3.05)	(10.17)	(27.02)	(18.17)
Term Loan	0.368***	0.405***	0.449***	0.468***
	(15.08)	(6.84)	(9.59)	(9.00)
Size	-0.217***	-0.262***	-0.254***	-0.103***
	(-11.29)	(-5.53)	(-7.55)	(-2.95)
Leverage	0.348***	0.521***	-0.088	0.051
	(5.52)	(3.71)	(-0.68)	(0.28)
MB	-0.052***	-0.035	0.006	0.027
	(-2.64)	(-1.00)	(0.16)	(0.81)
Profitability	-0.688***	-0.792**	-0.118	-0.175
	(-3.31)	(-2.51)	(-0.27)	(-0.39)
Funds	-0.317***	-0.275**	0.231	0.309*
	(-5.86)	(-1.99)	(1.09)	(1.94)
Tangibility	-0.254***	-0.330**	0.106	0.023
	(-3.96)	(-2.23)	(0.65)	(0.14)
Log IntCov	-0.114***	-0.203***	-0.041	-0.079***
	(-7.17)	(-6.94)	(-1.50)	(-3.21)
O-Score	0.024***	0.048***	0.009	0.017
	(3.59)	(2.97)	(0.75)	(1.17)
AbsAccr	0.008***	0.618***	0.217	0.508***
	(7.68)	(3.65)	(1.61)	(3.31)
Prior	-0.034	-0.100***	-0.105*	-0.097**
	(-1.48)	(-2.99)	(-1.65)	(-2.27)
Term Spread	0.086	-0.010	-0.014	-0.025
	(1.54)	(-0.18)	(-0.18)	(-0.39)
Credit Spread	0.249**	0.081	0.119	-0.204
	(2.52)	(0.85)	(1.05)	(-1.44)
Intercept	6.275***	1.410***	0.845*	-0.029
	(43.71)	(2.86)	(1.95)	(-0.07)
Loan Purpose Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes
No. of observations	11,088	11,088	11,088	11,088
Adj./Pseudo R^2	0.60	0.31	0.42	0.44

Notes: This table presents the estimated results of the effect of SPE use on loan contracting terms. Column (1) is for an OLS regression and columns (2)–(4) are for probit regressions. All variables are as defined in the Appendix. The *t*-statistics (*z*-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in a two-tailed test.

Table 5: Number of SPEs and Contracting: Subsample Analyses

Panel A: CEO Delta Risk								
Variable	**(1)** *AIS*		**(2)** *DSecu*		**(3)** *DFinCov*		**(4)** *DGenCov*	
	Low (I)	High (II)	Low (I)	High (II)	Low (I)	High (II)	Low (I)	High (II)
Log NSPE	0.014	0.062***	-0.008	0.090***	0.073**	0.088**	0.014	0.087**
	(0.92)	(4.47)	(-0.21)	(2.74)	(2.43)	(2.21)	(0.31)	(2.05)
Diff.	0.048***		0.098**		0.015		0.073*	
(II)-(I)	(3.06)		(2.00)		(0.34)		(1.81)	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,767	2,779	2,767	2,779	2,767	2,779	2,767	2,779
Panel B: Prior Lending Relationship								
	Yes (I)	No (II)	Yes (I)	No (II)	Yes (I)	No (II)	Yes (I)	No (II)
Log NSPE	0.028*	0.045***	0.036	0.087***	0.054***	0.137***	0.024	0.103***
	(1.93)	(5.03)	(1.30)	(4.22)	(2.69)	(4.16)	(0.77)	(3.57)
Diff.	0.017		0.051**		0.083**		0.079**	
(II)-(I)	(1.16)		(1.95)		(2.39)		(2.36)	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,131	5,957	5,131	5,957	5,131	5,957	5,131	5,957

Notes: This table presents the estimated results of the effect of SPE use on loan contracting terms partitioned based on the median of CEO delta risk and whether there is a prior lending relationship between the borrower and lender. Column (1) is for an OLS regression and columns (2)–(4) are for probit regressions. All variables are as defined in the Appendix. The *t*-statistics (*z*-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in a two-tailed test.

Table 6: Number of SPEs and Loan Contracting: PSM sample

Panel A: First Stage Probit Regression for PSM Method

	Pr (*DSPE*= 1)	
VARIABLES	Coefficients	*t*-statistics
LEV	0.707***	(5.70)
R_INTCOV	0.145***	(5.83)
BONUSP	0.126	(0.97)
DEBTISS	0.853***	(4.02)
STOCKISS	-0.687***	(-3.59)
RISK	-0.391***	(-2.82)
FUNDS	-0.004	(-0.02)
CLTD	-0.959***	(-2.69)
TDUM	0.103	(1.37)
SETR	0.198	(0.61)
INTANGIBLE	1.856***	(11.25)
FOREIGN	0.011	(0.18)
LMKTCAP	0.371***	(16.72)
INDPERC	3.280***	(10.03)
Constant	-5.057***	(-7.20)
Year Indicators	Yes	
No. of observations	22,747	
Pseudo R^2	0.207	

Panel B: PSM Sample

	(1)	(2)	(3)	(4)
VARIABLES	Log AIS	DSecu	DFinCov	DGenCov
Log NSPE	0.030***	0.058**	0.110**	0.062
	(3.33)	(2.21)	(2.41)	(1.25)
Control Variables	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes
No. of observations	4,318	4,318	4,318	4,318
Adj./Pseudo-R^2	0.68	0.37	0.53	0.61

Panel C: Within Firm Analyses

	(1)	(2)	(3)	(4)
VARIABLES	Log AIS	DSecu	DFinCov	DGenCov
AfterSPE	0.076***	0.204**	-0.181	-0.116
	(2.64)	(2.16)	(-1.29)	(-0.97)
	(21.28)	(4.90)	(0.51)	(1.98)
Control Variables	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes
No. of observations	2,343	2,343	2,343	2,343
Adj./Pseudo-R2	0.67	0.43	0.52	0.60

Notes: This table presents the results of the effect of SPE use on loan contracting terms using the PSM sample. Panel A reports the first-stage probit regression for predicting the likelihood of SPE formation. Panel B reports the estimated results of the effect of SPE use on loan contracting terms using the PSM sample. Panel C presents the estimated results of within-firm analysis using a sample of loan facilities borrowed by SPE firms around their first-time filing of SPEs in a 10-K. The test variable *AfterSPE* is an indicator variable that equals one when the loan facility is initiated after the borrower starts using SPEs and zero otherwise. For Panels B and C, Column (1) is for an OLS regression and columns (2)–(4) are for probit regressions. All variables are as defined in the Appendix. The *t*-statistics (*z*-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in a two-tailed test.

Table 7: Number of SPEs and Loan Contracting: Controlling for Credit Ratings

VARIABLES	(1) *Log AIS*	(2) *DSecu*	(3) *DFinCov*	(4) *DGenCov*
Log NSPE	0.030***	0.039*	0.086***	0.051**
	(3.25)	(1.87)	(4.24)	(1.99)
Rating	0.158***	0.303***	0.085***	0.094***
	(27.41)	(10.85)	(6.49)	(6.97)
Controls	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes
No. of observations	5,803	5,803	5,803	5,803
Adj./Pseudo R^2	0.77	0.49	0.50	0.58

Notes: This table presents the estimated results of the effect of SPE use on loan contracting terms after controlling for credit ratings. Column (1) is for an OLS regression and columns (2)–(4) are for probit regressions. All variables are as defined in the Appendix. The *t*-statistics (*z*-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in a two-tailed test.

Table 8: The Impact of SPE Use on Accounting Restatement and Future Credit Default

Panel A: Accounting Restatement

	Pr (MISSTATE = 1)	
VARIABLE	Estimator	z-statistics
Log $NSPE_t$	0.362***	(5.31)
DAR_t	1.422*	(1.91)
$DROA_t$	-0.911	(-1.53)
$DINVT_t$	3.195***	(3.94)
$RRST_t$	-0.172	(-0.61)
$ISSUE_t$	0.699	(1.58)
$DCSALE_t$	0.218***	(3.33)
PPE_AT_t	-2.440***	(-5.31)
Constant	-5.092***	(-10.68)
Year Indicators	Yes	
No. of Observations	27,079	
Pseudo R-Square	0.067	

Panel B: Observed Defaults

	Pr (DEFAULT = 1)	
VARIABLE	Estimator	z-statistics
Log $NSPE_t$	0.039	(0.46)
Log MktCap	-0.091*	(-1.91)
LEVERAGE	1.534***	(6.18)
Profitability	-4.927***	(-2.80)
Z-Score	-0.047**	(-2.14)
Term Spread	-0.172	(-0.93)
Credit Spread	0.544	(1.24)
Year Indicators	Yes	
Industry Indicators	Yes	
No. of Observations	6,676	
Pseudo R-Square	0.082	

Notes: This table reports the logistic regression results of the impact of SPE usage on accounting misstatement and credit default. The sample period is from 1996 to 2007. In Panel A, *MISSTATE* is an indicator that takes the value of 1 for misstatement firm years and 0 otherwise; *DAR* is the change in accounts receivable deflated by average total assets; *DROA* is the change in return on assets measured as income before extraordinary item deflated by average total assets; *DINVT* is the change in inventory deflated by average total assets; *RRST* is an accrual measure defined as the change in working capital plus the change in noncash net operating assets and the change of net financial assets deflated by average total assets; *ISSUE* is an indicator variable coded 1 if the firm issued securities during the year and 0 otherwise; *DCSALE* is the percentage change in cash sales; *PPE_AT* is PPE deflated by total assets. In Panel B, *DEFAULT* is an indicator that takes value of 1 if the firm experiences bankruptcy or defaults that do not result in a bankruptcy filing and zero otherwise; *Log MktCap* is the natural log value of market capitalization; *Z-score* is Altman's (1968) Z-score. All the other variables are as defined in Appendix I. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in a two-tailed test.

Table 9: Effect of Asset-backed Securitization on Loan Contracting

Panel A: First-Stage Probit Model

	Pr(*ABSDum* = 1)	
VARIABLES	Coefficients	z-statistics
Size	0.370***	(9.35)
AR	1.316***	(2.61)
Leverage	0.712*	(1.79)
Leverage^2	-0.300	(-0.79)
Rated	0.091	(0.69)
InvestGrade	0.081	(0.53)
BB	0.372***	(2.95)
Downgrade	-0.057	(-0.63)
Constant	-4.525***	(-7.20)
Year Indicators	Yes	
Industry Indicators	Yes	
No. of observations	6,255	
Pseudo R^2	0.23	

Panel B: Full Sample

	(1)	(2)	(3)	(4)
VARIABLES	*Log AIS*	*DSecu*	*DFinCov*	*DGenCov*
ABSDum	0.165***	0.207***	0.204***	-0.003
	(4.69)	(2.59)	(2.88)	(-0.04)
Adj. Leverage	0.357***	0.540***	-0.073	0.047
	(6.13)	(3.61)	(-0.58)	(0.25)
Controls	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes
No. of observations	11,088	11,088	11,088	11,088
Adj./Pseudo R^2	0.60	0.31	0.42	0.44

Panel C: PSM Sample

	(1)	(2)	(3)	(4)
VARIABLES	Log AIS	DSecu	DFinCov	DGenCov
ABSDum	0.161***	0.202*	0.206**	-0.061
	(4.26)	(1.76)	(2.26)	(-0.42)
Adj. Leverage	0.276**	1.626***	0.157	0.359
	(2.07)	(2.68)	(0.34)	(0.67)
Controls	Yes	Yes	Yes	Yes
Loan Purpose Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes
No. of observations	1,390	1,390	1,390	1,390
Adj./Pseudo R2	0.70	0.46	0.58	0.66

Notes: This table presents the estimated results of the effect of asset securitization on loan contracting terms. Panel A reports the estimated results of the first stage probit regression for predicting securitization. Panel B reports the estimated results of Eq. (1) using full sample. Panel C reports the estimated results of Eq. (1) using the PSM sample. In panels B and C, column (1) is for an OLS regression and columns (2)–(4) are for probit regressions. *ABSDum* is an indicator that equals one if the borrower reports securitization in its 10K and zero otherwise. The determinants used in the first stage probit model to predict securitization include: *AR*: account receivable divided by total assets; *Rated*: indicator variable that equals one if the borrower has an S&P Domestic Long-Term Issuer Credit Rating, and zero otherwise; *InvestGrade:* indicator variable that equals one if the borrower has an investment-grade S&P Domestic Long-Term Issuer Credit Rating (i.e., BBB- and above), and zero otherwise; *BB*: indicator variable that equals one if the borrower's S&P Domestic Long-Term Issuer Credit Rating is BB+, BB, or BB-, and zero otherwise; *Downgrade*: indicator variable if the borrower's current credit rating is worse than that last year. All other variables are as defined in the Appendix. The *t*-statistics (*z*-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in a two-tailed test.