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Does Information Technology Reputation Affect Bank Loan Terms?

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ABSTRACT: This study investigates whether Information Technology (IT) reputation, captured by the accumulation of consistent IT capability signals, influences bank loan contracting even though banks have access to inside information. We predict that IT reputation is associated with better loan terms because it lowers credit risk via its impact on default and information risks. Results based on 4,218 loan facility-years reveal, as predicted, that firms with a reputation for IT capability tend to have more favorable price and non-price terms for loan contracts and are less likely to have their credit rating downgraded or to report internal control weaknesses than firms with no IT reputation. The study contributes to the banking and IT business value literature by showing that banks incorporate borrowers' nonfinancial characteristics, such as IT reputation, into loan contracting terms.

Keywords: IT reputation; bank loans; signaling theory; default risk; information risk.

JEL Classifications: G21; G32; M41; O32.

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

I. INTRODUCTION

Information technology (IT) has become the backbone of most firms, and IT business value has emerged as one of the most important subjects in accounting information systems research (Sutton 2010). Researchers and IT professionals agree that IT capabilities positively affect a firm's financial performance and competitive position (Melville, Kraemer, and Gurbaxani 2004; Wade and Hulland 2004; Piccoli and Ives 2005; Mithas, Ramasubbu, and Sambamurthy 2011; Lim, Stratopoulos, and Wirjanto 2011). However, IT capabilities can be difficult for outside stakeholders to value because they are unobservable (Godfrey and Hill 1995; Lim et al. 2011). This information opaqueness incentivizes IT-capable firms to voluntarily signal their superior capability to outside stakeholders, such as investors and lenders, in order to build an IT capability reputation (Spence 1973; Connelly, Certo, Ireland, and Reutzel 2011). Our study investigates whether IT capability reputation can inform lenders about borrower credit risk and consequently influence loan contracting terms.

While previous studies identify how IT business value manifests in aggregate firm performance measures, such as accounting earnings and market value, they do not address the specific financial effects, such as borrowing costs, associated with IT capability (e.g., A. Bharadwaj, S. Bharadwaj, and Konsynski 1999; Brynjolfsson and Hitt 2003; Kobelsky, Richardson, Smith, and Zmud 2008). Borrower credit risk includes default risk and information risk, and we expect that IT capability lowers

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both. First, prior research finds that firms with IT capability invest more efficiently and effectively in IT, have higher and less volatile earnings, and face lower downside risk, suggesting lower default risk (e.g., Piccoli and Ives 2005; Mithas et al. 2011; Tian and Xu 2015). Second, the quality of credit risk information depends on the infrastructure of a borrower's internal information system (e.g., Costello and Wittenberg-Moerman 2011; Kim, Song, and Zhang 2011a). Prior research finds that firms with IT capability improve the internal information environment, suggesting lower information risk (Masli, Peters, Richardson, and Sanchez 2010; Dorantes, Li, Peters, and Richardson 2013; Chen, Smith, Cao, and Xia 2014). We study whether banks recognize IT capability when negotiating loan terms.

Although lenders have privileged access to borrowers' inside information, IT capability is unobservable and difficult to measure. A firm's appearance in the annual *InformationWeek* 500, a list of America's most IT-innovative firms (IW500), can help lenders with their due diligence by providing a means by which to verify the precision of their private information about borrowers' credit quality. IT managers voluntarily provide *InformationWeek* with detailed information about their IT practices. An editorial panel of IT business experts evaluates the information provided and selects the firms to be included in the annual IW500 list (Bharadwaj 2000). The process used by IW500 is consistent with signaling theory (Rindova 1997), and attributes of IW500 firms tend to map well into the theoretically expected characteristics of IT-capable firms (Lim et al. 2011, 55). The signaling literature suggests that consistent signals over time demonstrate a firm's superior competence, increase signaling effectiveness, and build firm reputation (Dierickx and Cool 1989; Rindova 1997; Barnett, Jermier, and Lafferty 2006; Pfarrer, Pollock, and Rindova 2010; Walker 2010; Connelly et al. 2011). Accordingly, we argue that appearance in the IW500 over five consecutive years establishes a firm's IT capability reputation (hereafter, IT reputation), and hypothesize that lenders reward such borrowers with lower interest rates and more favorable non-price terms.

To test our hypotheses, we examine the effect of IT reputation on loan interest rate, likelihood of loan being secured by collateral, and number of covenants after controlling for loan-specific characteristics (including loan type and loan purpose indicators), borrower-specific characteristics (including industry indicators), economy-wide factors, and year fixed effects. In addition to the traditional credit risk and performance variables (such as firm size, leverage, profitability), our borrower-specific controls include audit opinion, internal control weaknesses, future credit rating downgrade, IT spending, and corporate reputation.

Results based on 4,218 loan facility-years from 2002 to 2011 show that banks tend to charge significantly lower loan interest rates to, and impose more favorable non-price terms (collateral requirement and covenants) on, borrowing firms with IT reputation. In terms of economic significance, we find that the average interest rate is about 9 percent lower for loans to borrowers with, than without, IT reputation. It translates into an annual interest saving of $1.37 million for the average loan in our sample. In additional analyses, we confirm that IT reputation lowers one indicator of default risk (future credit rating downgrades) and one indicator of information risk (internal control weaknesses), consistent with our expectations. Thus, our primary analyses suggest that lenders find IT reputation useful, and our secondary analyses suggest that this usefulness stems from both default and information risk.

To alleviate endogeneity concerns, we extract both the treatment sample of firms with IT reputation and the control sample of firms without IT reputation from the same population of IW500 firms. All firms have signaled their IT capability (i.e., they have appeared in the IW500 list) at least once over the sample period. This mitigates a concern about potential self-selection and/or simultaneity bias. However, to alleviate concerns that our sample selection procedure does not sufficiently address endogeneity, we apply the following four empirical approaches: (1) Heckman's (1979) two-stage treatment effect regressions; (2) propensity score matching (PSM); (3) firm fixed effects regressions; and (4) changes regressions. Using these approaches does not alter our main inferences.

Our study makes multiple contributions to the existing literature. First, this paper extends the IT business value literature. Whereas prior literature investigates the effect of IT on aggregate firm earnings and market values, this paper takes the next step by examining cost-reduction effects of IT-based informational improvements on the borrowing cost. It, thus, begins to disaggregate IT's effects on a firm and responds to the call by accounting information systems scholars to extend the IT business value research (Dehning and Richardson 2002; Masli, Richardson, Sanchez, and Smith 2011). Given that we include both IT reputation and IT spending in our analysis, our study further extends the literature by providing evidence on the relative effects of IT quality (reputation) versus IT quantity (spending).

Second, this study adds to the banking literature by providing evidence supporting the proposition that banks do indeed value nonfinancial characteristics, such as a firm's IT reputation, and factor them into both the price and non-price terms of loan contracts. Financial institutions are under attack from the so-called Fintech revolution (*The Economist* 2015). Fintech firms are capable, among other things, of assessing credit risk by performing various forms of text/sentiment analytics based on nonfinancial data. While the importance of nonfinancial information in accounting in general and in banking in particular has been growing, few bank loan studies have examined whether and how loan contracting terms are affected by borrowers' nonfinancial characteristics (i.e., information not directly available from financial reports).

Finally, our study adds to the corporate reputation literature by introducing a new value proposition associated with IT reputation. Of particular importance is our finding that firms with IT reputation enjoy more favorable loan terms, and are less likely to have internal control weaknesses, even after controlling for overall corporate reputation. The above results, thus, complement and extend the evidence provided by Cao, Myers, and Omer (2012) and Cao, J. Myers, L. Myers, and Omer (2015) on the effect of corporate reputation on the cost of equity and financial reporting quality. Our analysis shows that the effect of IT reputation goes beyond that captured by overall corporate reputation.

The paper proceeds as follows. Section II reviews the relevant literature and develops our hypotheses. Section III describes our research design. Section IV explains our sample selection procedures and presents descriptive statistics. Section V provides the results of our main regressions, and Section VI provides additional tests. Section VII concludes.

II. RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

Background

Corporate reputation—the accumulated public recognition of the quality of a firm's capability or products/services—is a strategic priority for managers and a growing area of research (Rindova 1997; Rindova, Williamson, Petkova, and Sever 2005; Barnett et al. 2006; Walker 2010). Using *Fortune*'s list of America's most admired companies as a proxy, prior research has linked corporate reputation to profitability (Roberts and Dowling 2002), stock market returns, cost of equity (Filbeck and Preece 2003; Anderson and Smith 2006; Cao et al. 2015), and financial reporting quality (Cao et al. 2012). However, in most cases, a firm's reputation tends to be issue-specific (Walker 2010). The strategic role of IT in modern firms and the growing recognition of the value of IT capabilities (e.g., Melville et al. 2004; Wade and Hulland 2004; Piccoli and Ives 2005) motivate us to focus on IT reputation as an issue-specific type of corporate reputation.

Development of a firm's IT reputation is a dynamic process that involves the focal firm, intermediaries, and interested stakeholders (Rindova 1997). Firms that have achieved a minimum level of IT capability are able to credibly signal their IT capability to stakeholders (Staw and Epstein 2000). "Efficacious signals" should be observable and costly (Connelly et al. 2011, 45). Firms that signal their IT capability through the IT business press spend, on average, \$50–\$90 million per year in new IT products and services (Stratopoulos and Lim 2010). Furthermore, firms that want to build an IT reputation must maintain signal consistency over several consecutive years (Connelly et al. 2011; Gao, Darroch, Mather, and MacGregor 2008). In addition to this, IT project implementation remains challenging, and extracting value from new IT initiatives requires the ability to effectively adopt, deploy, and integrate IT resources with other organizational resources and managerial processes (e.g., Bharadwaj 2000; Lim et al. 2011; Stratopoulos and Dehning 2000). In sum, IT reputation building is costly, time-consuming, and difficult for firms without the underlying IT capability to imitate (Dierickx and Cool 1989; Rindova 1997; Barnett et al. 2006; Pfarrer et al. 2010; Walker 2010).

Intermediaries (the IT business press) select, evaluate, and choose which of these firm-projected signals they wish to transmit. Given the technical expertise of IT business press reporters, the IT business press amplifies firms' projected signals and makes them observable and more authoritative (Rindova 1997). We expect that stakeholders form their beliefs regarding a firm's IT reputation as follows (Rindova et al. 2005): (1) Firms that project consecutive and consistent IT capability signals communicate sustained IT capability. Therefore, these firms develop IT reputation; (2) Firms that project an IT capability signal only occasionally, or not at all, communicate an ambiguous message. Stakeholders of these firms do not know if the lack of signal or signal discontinuity arises because these firms are not interested in projecting a signal or because they have not achieved a minimum level of IT capability. This ambiguity prevents stakeholders from forming beliefs regarding the sustainability of these firms' IT capability, and hence these firms do not go on to develop IT reputation.

Hypotheses Development

We expect that lenders (stakeholders) will process IT capability signals if such signals help them develop more accurate beliefs about the conditional probability distribution of firms' credit risk (Spence 1973). On the one hand, several studies suggest that banks have a superior ability to collect and process information about borrowers' credit risk (Fama 1985; Rajan 1992; Cole 1998; Denis and Mihov 2003). One might, therefore, argue that lenders gain little incremental benefit by processing public IT capability signals. Therefore, lenders may not process IT capability signals and IT reputation will not affect loan contracting.

On the other hand, lenders might indeed be interested in processing public signals of a borrower's IT capability for several reasons. First, prior literature finds that firms with IT capability make more efficient and effective IT investments, and are better able to exploit business opportunities and/or neutralize threats than firms without IT capability (e.g., Melville et al. 2004; Wade and Hulland 2004; Piccoli and Ives 2005; Mithas et al. 2011). As a result, firms with IT capability have higher and less volatile expected future earnings, face lower downside risk, and recover more quickly from negative earnings during a recession (e.g., Chen, Lim, and Stratopoulos 2011; Otim, Dow, Grover, and Wong 2012; Tian and Xu 2015). Therefore, banks could recognize that firms with IT capability should have lower default risk than firms without IT capability and, as a result, offer better lending terms to firms with IT reputation.

Second, recent bank loan studies suggest that access to inside information cannot help banks entirely overcome problems related to borrowers' information opaqueness (e.g., Bharath, J. Sunder, and S. Sunder 2008; Graham, Li, and Qiu 2008; Costello and Wittenberg-Moerman 2011; Kim et al. 2011a). Inside information, such as details about ongoing operating decisions and their potential impact on future firm performance, is generated by borrowers' information systems. The quality of that inside information, therefore, depends on the infrastructure of a borrower's internal information system and its IT capability. Prior IT literature shows that firms that invest in internal control monitoring technology, implement enterprise resource planning systems, or signal an IT capability tend to see improvements in their internal information environments, indicated by a lower likelihood of internal control weaknesses and greater accuracy in management earnings forecasts (e.g., Masli et al. 2010; Dorantes et al. 2013; Chen et al. 2014). Therefore, banks could recognize that firms with IT capability should have lower information risk than firms without IT capability and, as a result, offer better lending terms to firms with IT reputation.

Third, IT capability is unobservable and, thus, is difficult to measure. While private information regarding a firm's IT initiatives (e.g., IT investments, human capital, and investment in IT complementary resources) might help lenders identify elements that form the foundation of an IT capability, this is not enough to understand and measure a borrower's IT capability. An observable signal of IT capability, initiated by borrowers and confirmed by the professional IT business press, potentially helps lenders verify the precision of their private information about borrowers, provides lenders with a summary measure of IT capability, and facilitates lenders conducting due diligence to know their customers.[1]

Therefore, we expect lenders to view IT reputation as a credible indicator of borrowers' IT capability, use it to evaluate borrowers' credit risk, and factor it into loan interest rates and non-price loan terms. We state our first hypothesis in alternative form as follows:

H1a: *Ceteris paribus,* banks charge lower loan rates to borrowers with IT reputation than to those without IT reputation.

H1b: *Ceteris paribus,* banks are less likely to require collateral and tend to impose fewer restrictive covenants on loans for borrowers with IT reputation than for those without IT reputation.

When developing H1a and H1b, we posit that lenders value a borrower's IT reputation because it credibly signals a borrower's credit risk, i.e., default risk and/or information risk. To support our theory, we further consider whether IT reputation does indeed predict default risk and information risk.

Default risk is the risk associated with the likelihood that borrowers are unable to meet their loan obligations, such as interest payments and principal repayment at maturity. To validate our assumption that IT reputation signals lower default risk, we test the association between IT reputation and downgrades of a borrower's credit rating. Credit rating agencies are crucial information intermediaries in the capital market, and their assessment of firms' default risk has a significant effect on debt contract terms. Based on the development of H1a and H1b above, we expect that firms with IT reputation experience fewer credit rating downgrades than firms without IT reputation, stated in alternative form as follows:

H2a: *Ceteris paribus,* the likelihood of credit rating downgrade is lower for firms with IT reputation than for those without IT reputation.

Information risk is the risk associated with the imperfect information that lenders use to estimate borrowers' future cash flows (e.g., Duffie and Lando 2001; Bharath et al. 2008; Graham et al. 2008; Kim et al. 2011a). To validate our assumption that IT reputation signals lower information risk, we test the association between IT reputation and the presence of internal control weaknesses (ICWs) disclosed under the Sarbanes-Oxley Act of 2002 (SOX). The existence of ICWs is an appropriate proxy for information risk in the context of bank loan contracting, because the literature suggests that ICWs have a negative effect on the quality of firms' inside information used by managers and conveyed to lenders (Feng, Gramlich, and Gupta 2009; Kim et al. 2011a). Based on the development of H1a and H1b above, we expect that firms with IT reputation experience fewer ICWs than firms without IT reputation, stated in alternative form as follows:

H2b: *Ceteris paribus,* the likelihood of having internal control weaknesses (ICWs) is lower for firms with IT reputation than for those without IT reputation.

[1] The Export-Import Bank of the United States (EXIM) requires lenders to search news databases in order to collect information about their customers. This is part of the due diligence process and "know-your-customer" practices (see: http://www.exim.gov/policies/due-diligence-standards).

III. RESEARCH DESIGN

Measure of IT Reputation

InformationWeek has been ranking IT users since the late 1980s. *InformationWeek* invites IT user firms to fill out a questionnaire detailing their IT strategies, plans, and practices. Firms can choose to signal their IT capability by participating in the IW500 survey. Based on the survey information provided, the editorial panel of *InformationWeek* selects and ranks firms that will be included in the annual *InformationWeek* 500 (IW500) list. The list has been widely used in accounting and information systems research (e.g., Bharadwaj 2000; Kobelsky et al. 2008; Stratopoulos and Lim 2010).

While prior research supports the use of the IW500 as a signal of IT capability, we expect that IT reputation takes time to develop. Prior research finds that firms projecting consecutive signals of IT capability for three to five years are more likely to continue sending similar signals in future years (Lim et al. 2011; Lim, Stratopoulos, and Wirjanto 2013). Further, the estimated average duration of an IT-enabled competitive advantage is around five years (Dehning and Stratopoulos 2003). Therefore, we define *IT Reputation* as an indicator variable that equals 1 if the borrower is recognized in the IW500 for five consecutive years (the year when the loan is initiated and the previous four years), and 0 otherwise.

Empirical Model

To provide empirical evidence on the role of IT reputation in loan contracting, we specify the following regression model (all variables are defined in Appendix A):

$$\begin{aligned} Loan\ Feature = f(&IT\ Reputation, Loan\text{-}Specific\ Control, Borrower\text{-}Specific\ Control, Economy\text{-}Wide\ Control,\\ &Loan\ Type\ Indicator, Loan\ Purpose\ Indicators, Year\ Indicators, Industry\ Indicators) \end{aligned} \tag{1}$$

In the above model, the dependent variable, *Loan Feature* in year *t,* refers to one of the following features of a loan contract for a borrower *i*'s facility *k* in year *t: Log AIS, DSecu, FinCovIdx,* and *GenCovIdx. Log AIS* is a proxy for the interest cost of borrowing. We measure it by the natural log of the drawn all-in spread plus the upfront fee and annual fee, in basis points in excess of the London Interbank Borrowing Rate (LIBOR). *DSecu* is an indicator variable that equals 1 if the loan is secured with collateral, and 0 otherwise. *FinCovIdx* and *GenCovIdx* are financial and general covenant indices, respectively. We construct these two indices by counting the number of financial covenants and general covenants included in a loan contract, respectively. *IT Reputation* is defined above.

When *Log AIS* is the dependent variable, we estimate Equation (1) using ordinary least squares (OLS) regression; when *DSecu* is the dependent variable, we estimate Equation (1) using probit regression; and when *FinCovIdx* or *GenCovIdx* is the dependent variable, we estimate Equation (1) using Poisson regression. Following prior bank loan literature, we merge bank loan data with financial statement data for the fiscal year before loans are initiated (e.g., Dennis, Nandy, and Sharpe 2000; Bharath et al. 2008; Ivashina 2009).

Control Variables

Following prior literature, we include in Equation (1) the following set of loan-specific control variables: maturity (*Log Maturity*), amount (*Log Loan Size*), number of lenders (*Log NLenders*), existence of performance pricing provisions (*Performance Pricing*), and the number of prior loan deals between the borrower and the lead lenders (*Log NPriorDeals*) (e.g., Bharath et al. 2008; Graham et al. 2008; Kim et al. 2011a; Kim, Tsui, and Yi 2011b; Lin, Ma, Malatesta, and Xuan 2011). Graham et al. (2008) show that lenders charge lower loan rates for loans with shorter maturity, larger amounts, more lenders, performance pricing provisions, and prior borrower-lender relationships. We impose collateral requirements and covenant restrictions at the deal level rather than at the facility level.[2] We, therefore, replace *Log Loan Size* with *Loan Concentration* (the dollar amount of the loan deal divided by the sum of the loan deal amount plus the borrower's total liabilities) when *DSecu, FinCovIdx,* or *GenCovIdx* is used as the dependent variable.

We control for a set of borrower-specific variables that are known to affect credit quality and, thus, loan contracting terms: firm size (*Size*), leverage ratio (*Leverage*), market-to-book ratio (*MB*), historical profitability (*ProfitAvg*), profit volatility (*ProfitVol*), asset tangibility (*Tangibility*), Ohlson's (1980) O-score (*O-Score*), abnormal accruals (*Accr*), and numerical value of Standard & Poor's Domestic Long-Term Issuer Credit Rating (*S&P*). We expect that *Size, MB, ProfitAvg,* and *Tangibility* are positively associated with a borrower's credit quality, while *Leverage, O-Score, Accr,* and *S&P* are

[2] Each deal, which is a loan contract between a borrower and bank(s) at a specific date, can have only one facility or a package of several facilities with different price and nonprice terms. For example, a deal can comprise a line of credit facility and a term loan with different interest rates.

negatively associated with credit quality. Considering that the external auditor's audit opinion may provide information on a firm's IT capability, we also control the audit opinion (*CleanAUOP*) in our model. We measure the above financial statement variables and the credit rating in the fiscal year immediately before loans are initiated (i.e., year $t-1$), which ensures that these variables are observable to lenders when contracting with borrowers. As discussed in the hypotheses development section, we predict that IT reputation influences bank loan contracting through the default risk and information risk channels. We also include in the model the indicators of default and information risk (i.e., *Future Downgrade* and *ICW*) used to test H2a and H2b.

Previous IT studies have documented the link between IT spending and firm risk/performance (Dewan, Shi, and Gurbaxani 2007; Kobelsky et al. 2008; Henderson, Kobelsky, Richardson, and Smith 2010). Moreover, a firm's IT spending helps to build its IT reputation. To provide evidence on the impact of IT reputation on loan contracting terms over and above that of IT spending, we include in the model borrowers' IT spending scaled by sales in year $t-1$ (*IT Spending*).[3] The IT literature suggests that IT-capable firms are likely to have better operating performance and stock market valuation (Melville et al. 2004; Wade and Hulland 2004; Piccoli and Ives 2005). To isolate the effect of IT reputation from that of future financial and stock performance, we control for borrower profitability and market-to-book ratio measured in the loan initiation year (i.e., year t). Because a firm's IT reputation can be closely related to its general corporate reputation, we include corporate reputation (*Fortune*) in the loan initiation year as another control variable.

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. Finally, we include *Loan Type Indicators* and *Loan Purpose Indicators* to control for potential differences in the price and non-price terms of loan contracts associated with different loan types and purposes, respectively. We also include *Year Indicators* and *Industry Indicators* to control for potential differences in loan features over years and across industries.

IV. SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

Sample and Data

Our initial sample includes all publicly traded U.S. firms that have appeared at least once in the IW500 list from 1997 to 2011. Therefore, both the treatment group (firms with IT reputation) and the control group (firms with no IT reputation) belong to the population of firms that have signaled their IT capability at least once during this period. The IW500 also provides IT spending data. When a firm is not in the IW500 list for a certain year and, accordingly, its IT spending information is unavailable, we use the industry-level IT spending reported by the IW500 as a proxy for firm-level IT spending.[4] The bank loan data for these firms come from the Loan Pricing Corporation's (LPC) DealScan database. We require that all loan facilities in our sample be senior debts. With regard to the types of loans, our sample includes term loans, revolving loans, 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 obtain borrowers' financial statement and credit rating data from Compustat, and we extract the internal control data from Audit Analytics. We measure borrowers' IT reputation in a five-year window, i.e., the year when the loan is initiated, along with the previous four years; therefore, our IT reputation measure is available from 2001 to 2011. We start our sample period in 2002, however, because that is the first year for which internal control data are available.

Panel A of Table 1 presents the distribution of our sample firms and loan facilities by year. The number of borrowers and loan facilities dramatically decreases due to the financial crisis. In total, our final sample consists of 2,768 firm-years and 4,218 facility-years.[5] Panel B of Table 1 describes the frequency of our sample firms appearing over the sample period. Among our sample firms, 85 firms appear in one year only, 127 firms appear in five different sample years, and only one firm appears in all the ten years. Panel C of Table 1 presents the distribution of our treatment sample (i.e., observations with IT reputation) by Fama and French 48 industry classification. Here, 148 firms from 33 industries are classified as having IT reputation, and these firms have 448 loans in our sample. Business services, wholesale, utilities, and chemicals have more than ten firms with IT reputation, while eight industries (beer and liquor, recreation, rubber and plastic products, etc.) have only one firm with IT reputation.

[3] It may take some time for IT spending to manifest its positive effect in building IT reputation. In this sense, IT reputation in year t (i.e., our test variable) is subject to the influence by the IT spending in year $t-1$ more than that in year t. Nevertheless, our inferences remain unchanged if we measure IT spending in year t.
[4] Given that our sample firms enter and exit the IW500 list from one year to another, this procedure is necessary to maintain a reasonable sample size.
[5] Each loan facility is included in our sample only at its initiation.

TABLE 1
Sample Distribution

Panel A: Distribution of Firms and Loan Facilities by Year

Year	Firms	Facilities
2002	342	507
2003	363	547
2004	405	605
2005	345	551
2006	304	483
2007	296	511
2008	146	197
2009	110	156
2010	171	262
2011	286	399
Total	2,768	4,218

Panel B: Distinct Firms Appearing in the Sample for Different Numbers of Years

Years	Firms	Percent
1	85	12.01
2	100	14.12
3	132	18.64
4	119	16.81
5	127	17.94
6	72	10.17
7	47	6.64
8	20	2.82
9	5	0.71
10	1	0.14
Total	708	100.00

(continued on next page)

Descriptive Statistics and Correlations

Panel A of Table 2 presents descriptive statistics for the main loan characteristics by year. We find that, overall, the mean drawn all-in spread is smooth over time, but it significantly increases in the post-crisis period, i.e., from 2008 to 2011. The average amount of loan facility is highest in 2007 (946 million) and lowest in 2009 (400 million).

Panel B of Table 2 reports the loan-specific and borrower-specific variables for the full sample. The mean and median of the drawn all-in spread over the LIBOR (i.e., *AIS*) are around 165 and 125 basis points (bps), respectively. The mean (median) maturity is about 46 (60) months, while the mean (median) facility size is $687 million ($375 million). The table also shows that 37.4 percent of the loan facilities in our sample are secured by collateral, and 53.9 percent of them have performance pricing provisions. The *Loan Concentration* ratio indicates that the size of a loan deal is, on average, about 21.8 percent of the sum of the loan deal amount plus a borrower's total liabilities. The average loan in our sample includes about one financial covenant and nearly three general covenants. Most of the loan facilities in our sample are syndicated loans that have, on average, about 12 lenders. With respect to the prior borrower-lender relationship, a borrower in our sample has, on average, about one previous loan deal in the past five years with the lead arrangers for the current loan.

As shown in Table 2, Panel B, about 11 percent of loan borrowers in our sample have appeared in the IW500 over five consecutive years (the year of loan initiation and the previous four years). *Size* has its mean and median of 8.40 and 8.37, respectively, with a standard deviation of 1.44. The mean (median) market-to-book ratio is 1.73 (1.44), and the mean (median) *O-Score* is −7.03 (−7.13). On average, debt, earnings before interest, taxes, depreciation, and amortization (EBITDA), and tangible assets (i.e., PP&E) are about 67 percent, 14 percent, and 32 percent of total assets, respectively. The proxy for accounting quality (*Accr*) has the mean (median) of 0.09 (0.04). The mean value of *S&P* (i.e., 12.4) indicates that the average firm in our sample has an S&P Long-Term Issuer Credit Rating between BB and BB−, and 38.9 percent of the borrowers in our

TABLE 1 (continued)

Panel C: Distribution of Observations with IT Reputation by Industry

Fama-French 48 Industry Code	Industry Name	Number of Unique Firms	Number of Firm-Years	Number of Loans
2	Food Products	3	6	9
4	Beer and Liquor	1	1	1
6	Recreation	1	1	2
7	Entertainment	2	8	16
8	Printing and Publishing	3	5	6
9	Consumer Goods	4	12	19
10	Apparel	3	4	4
11	Healthcare	5	10	14
13	Pharmaceutical Products	4	11	16
14	Chemicals	11	28	37
15	Rubber and Plastic Products	1	2	7
17	Construction Materials	6	16	25
18	Construction	2	3	4
19	Steel Works	2	3	3
21	Machinery	5	8	9
22	Electrical Equipment	2	7	17
23	Automobiles and Trucks	3	4	6
28	Non-Metallic and Industrial Metal Mining	1	5	7
30	Petroleum and Natural Gas	3	5	6
31	Utilities	11	28	43
32	Communication	4	12	14
33	Personal Services	1	5	5
34	Business Services	18	36	49
35	Computers	7	11	11
36	Electronic Equipment	5	9	13
37	Measuring and Control Equipment	1	2	2
38	Business Supplies	6	11	12
39	Shipping Containers	1	3	3
40	Transportation	9	23	30
41	Wholesale	12	22	27
42	Retail	8	15	18
43	Restaurants, Hotels, Motels	2	9	10
48	Others	1	3	3
Total		148	328	448

sample receive an unqualified audit opinion without explanatory language from their external auditors.[6] The percentage of borrowers reporting ICWs under SOX Section 302 is 6.3 percent, and 31.9 percent of the borrowers experience at least one credit rating downgrade within the following three years. Average IT spending accounts for 2.7 percent of sales revenue for our sample firms. About 35 percent of borrowers in our sample have appeared in the list of *Fortune*'s Most Admired companies.

Panel C of Table 2 compares the main loan and firm characteristics of borrowers with IT reputation (*IT Reputation* = 1) with those without IT reputation (*IT Reputation* = 0). Consistent with H1a and H1b, we find that loans to borrowers with IT reputation have lower interest rates, include fewer covenants, and are less likely to have the loans secured by collateral. Panel C also shows that borrowers with IT reputation are less likely to have internal control weaknesses and a credit rating downgrade in the subsequent three years, which is in line with H2a and H2b, respectively.

Table 3 reports Pearson correlation coefficients among selected loan- and borrower-specific variables. Consistent with our predictions, we find that *IT Reputation* is significantly and negatively correlated with *Log AIS* (–0.127), *DSecu* (–0.141), *FinCovIdx* (–0.084), and *GenCovIdx* (–0.092). Although only indicative of the underlying relations, the above correlations

[6] Among 4,218 loans in our sample, 1,642 borrowers receive an unqualified opinion without explanatory language on their financial statements, 2,575 receive an unqualified opinion with explanatory language, and only one borrower receives a qualified opinion.

TABLE 2

Descriptive Statistics

Panel A: Means of Main Loan Characteristics by Year

Year	n	*AIS* (bps)	*Maturity* (months)	*Loan Size* (millions $)	*DSecu*	*FinCovIdx*	*GenCovIdx*	*NLenders*
2002	507	150.249	28.509	540.298	0.286	1.479	2.631	13.026
2003	547	166.935	33.828	464.317	0.389	1.717	3.046	13.843
2004	605	139.089	46.693	600.509	0.357	1.597	3.045	14.025
2005	551	120.078	52.298	703.778	0.339	1.523	3.015	12.016
2006	483	137.027	55.176	877.953	0.402	1.449	3.416	11.621
2007	511	130.525	57.325	945.521	0.421	1.219	3.235	11.548
2008	197	188.172	41.142	755.948	0.406	1.482	3.431	9.888
2009	156	378.561	37.308	399.559	0.532	1.622	3.404	8.429
2010	262	277.601	49.118	634.775	0.431	1.248	2.45	13.023
2011	399	189.698	57.383	835.249	0.326	0.947	1.596	11.536

Panel B: Loan and Borrower Characteristics for Full Sample

Variables	Mean	1st Quartile	Median	3rd Quartile	Std. Dev.
AIS (bps)	164.825	55.000	125.000	225.000	141.864
Maturity (months)	46.386	34.000	60.000	60.000	22.364
Loan Size (millions $)	686.829	170.000	375.000	800.000	1123.181
Loan Concentration	0.218	0.087	0.168	0.310	0.172
DSecu	0.374	0.000	0.000	1.000	0.484
FinCovIdx	1.438	0.000	1.000	2.000	1.309
GenCovIdx	2.914	0.000	3.000	4.000	2.784
Performance Pricing	0.539	0.000	1.000	1.000	0.499
NLenders	12.346	6.000	10.000	17.000	9.885
NPriorDeals	1.396	0.000	1.000	2.000	2.191
IT Reputation	0.106	0.000	0.000	0.000	0.308
Size	8.399	7.434	8.366	9.497	1.439
Leverage	0.667	0.515	0.639	0.762	0.265
MB	1.726	1.168	1.443	1.960	0.904
ProfitAvg	0.142	0.097	0.131	0.178	0.075
ProfitVol	0.032	0.013	0.023	0.040	0.032
Tangibility	0.324	0.142	0.276	0.496	0.218
O-Score	−7.031	−8.137	−7.133	−6.188	1.969
Accr	0.086	0.017	0.044	0.102	0.117
S&P	12.380	8.000	11.000	15.000	6.106
CleanAUOP	0.389	0.000	0.000	1.000	0.488
ICW	0.063	0.000	0.000	0.000	0.244
Future Downgrade	0.319	0.000	0.000	1.000	0.466
IT Spending	0.027	0.019	0.021	0.031	0.024
Fortune	0.352	0.000	0.000	1.000	0.478

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provide support to our research hypotheses H1a and H1b. Consistent with H2a and H2b, *IT Reputation* is significantly and negatively correlated with the existence of ICWs (*ICW*) and future credit rating downgrades (*Future Downgrade*).

V. MAIN RESULTS

The Impact of IT Reputation on Price and Non-Price Loan Contract Terms

Table 4 reports the results of estimating Equation (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

TABLE 2 (continued)

Panel C: Comparisons of Main Variables between Borrowers With and Without IT Reputation

	IT Reputation = 0 (n = 3,770)		*IT Reputation* = 1 (n = 448)		Test of Difference	
Variables	**Mean**	**Median**	**Mean**	**Median**	**t**	**z**
AIS (bps)	169.998	150.000	121.287	75.000	6.91***	8.32***
Maturity (months)	46.532	60.000	45.158	60.000	1.23	0.55
Loan Size ($ millions)	659.579	350.000	916.140	500.000	−4.58***	−7.25***
Loan Concentration	0.222	0.170	0.183	0.157	4.52***	3.47***
DSecu	0.397	0.000	0.176	0.000	9.22***	9.13***
FinCovIdx	1.476	2.000	1.121	1.000	5.45***	4.95***
GenCovIdx	3.002	3.000	2.174	2.000	5.98***	5.74***
Performance Pricing	0.539	1.000	0.533	1.000	0.23	0.23
NLenders	12.175	10.000	13.779	12.000	−3.25***	−4.85***
NPriorDeals	1.363	1.000	1.676	1.000	−2.86***	−3.35***
Size	8.343	8.300	8.872	8.749	−7.39***	−7.05***
Leverage	0.669	0.639	0.654	0.646	1.10	0.66
MB	1.720	1.435	1.773	1.491	−1.18	−2.77***
ProfitAvg	0.141	0.130	0.150	0.147	−2.50**	−3.94***
ProfitVol	0.033	0.023	0.026	0.022	4.36***	4.34***
Tangibility	0.323	0.275	0.331	0.284	−0.71	−0.42
O-Score	−6.995	−7.092	−7.329	−7.322	3.40***	4.65***
Accr	0.086	0.044	0.081	0.041	0.84	0.83
S&P	12.646	11.000	10.141	9.000	8.27***	9.51***
CleanAUOP	0.394	0.000	0.348	0.000	1.89*	1.89*
ICW	0.066	0.000	0.045	0.000	1.72*	1.72*
Future Downgrade	0.327	0.000	0.257	0.000	3.00***	3.00***
IT Spending	0.027	0.021	0.030	0.021	−2.57**	−0.99
Fortune	0.333	0.000	0.511	1.000	−7.49***	−7.45***

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
All variables are defined in Appendix A.

coefficient on *IT Reputation* is negative and statistically significant at the 1 percent level (–0.098, t = −3.18), consistent with H1a. The estimated economic effect of IT reputation on lowering loan rates is around $1.37 million per year.[7]

Column (2) of Table 4 reports the results of a probit regression in which the dependent variable is the indicator for the presence of collateral requirement (*DSecu*). We find that the coefficient on *IT Reputation* is also negative and statistically significant at the 1 percent level (–0.439, z = −3.31). The negative coefficient suggests that IT reputation decreases the likelihood of loans being secured by collateral. Because *FinCovIdx* and *GenCovIdx* count the number of financial and general covenants, respectively, we estimated Equation (1) by applying Poisson regression procedure when the dependent variables are *FinCovIdx* and *GenCovIdx* in Columns (3) and (4), respectively. We find that the coefficients on *IT Reputation* are –0.114 (z = –2.03) and −0.122 (z = −1.78), significant at the 5 percent and 10 percent levels, respectively. The results in Columns (2)–(4) are consistent with H1b.

The results presented in Table 4 suggest that lenders find IT reputation useful, and IT reputation has a direct effect on loan terms. This direct effect is incrementally significant over and beyond our proxies for default risk and information risk, as well as future accounting performance and market value.

[7] The magnitude of the coefficient on *IT Reputation* suggests that, compared to borrowers without IT reputation, those with IT reputation enjoy about 9 percent lower loan interest rates, with all other *AIS* determinants unchanged. The calculations are as follows: $Log\ AIS_{ITReputation=1} - Log\ AIS_{ITReputation=0} = -0.098$. Thus, $AIS_{ITReputation=1} \div AIS_{ITReputation=0} = e^{-0.098} = 0.9067$. As reported in Table 2, the average all-in spread is 165 bps, and an average loan facility borrowed by firms with IT reputation is about $916 million with the maturity of 45 months. Our results imply that the drawn all-in spread of a loan with the same features borrowed by a firm with IT reputation is about 15 bps (165 bps × 9 percent) lower than that of the loan to the borrower without IT reputation, which means an annual interest saving of $1.37 million ($916 million × 15 bps) over about four years.

TABLE 3
Pearson Correlation Matrix

Panel A: Pearson Correlation Matrix for *IT Reputation* to *Size*

	IT Reputation	*Log AIS*	*DSecu*	*FinCovIdx*	*GenCovIdx*	*Log Maturity*	*Log Loan Size*	*Log NLenders*	*Performance Pricing*	*Log NPriorDeals*	*Size*
IT Reputation	1										
Log AIS	−0.127***	1									
DSecu	−0.141***	0.554***	1								
FinCovIdx	−0.084***	0.291***	0.414***	1							
GenCovIdx	−0.092***	0.370***	0.596***	0.714***	1						
Log Maturity	−0.014	0.212***	0.204***	0.163***	0.179***	1					
Log Loan Size	0.111***	−0.376***	−0.255***	−0.210***	−0.160***	0.041***	1				
Log NLenders	0.070***	−0.248***	−0.161***	0.054***	0.032**	0.074***	0.512***	1			
Performance Pricing	−0.004	−0.082***	0.033**	0.455***	0.354***	0.077***	0.054***	0.232***	1		
Log NPriorDeals	0.053***	−0.200***	−0.145***	−0.117***	−0.117***	−0.071***	0.172***	0.140***	−0.033**	1	
Size	0.113***	−0.335***	−0.326***	−0.373***	−0.310***	−0.134***	0.684***	0.393***	−0.102***	0.184***	1
Leverage	−0.017	0.299***	0.205***	0.016	0.071***	0.006	−0.008	−0.045***	−0.152***	−0.002	0.076***
MB	0.018	−0.325***	−0.134***	−0.065***	−0.078***	−0.041***	−0.035**	−0.072***	−0.018	−0.014	−0.165***
ProfitAvg	0.038**	−0.347***	−0.234***	−0.036**	−0.090***	−0.060***	0.068***	0.076***	0.065***	0.001	−0.099***
ProfitVol	−0.067***	0.139***	0.165***	0.077***	0.098***	−0.02	−0.227***	−0.230***	−0.030*	−0.072***	−0.295***
Tangibility	0.011	0.025	−0.068***	−0.144***	−0.093***	−0.051***	0.157***	0.090***	−0.065***	0.049***	0.291***
O-Score	−0.052***	0.422***	0.300***	0.129***	0.165***	0	−0.199***	−0.130***	−0.112***	−0.057***	−0.155***
Accr	−0.013	0.091***	0.106***	0.02	0.054***	0.006	−0.091***	−0.109***	−0.093***	−0.035**	−0.103***
S&P	−0.126***	0.508***	0.382***	0.298***	0.270***	0.196***	−0.484***	−0.334***	0.012	−0.178***	−0.609***
CleanAUOP	−0.029*	−0.036**	−0.050***	−0.008	−0.067***	0.017	−0.052***	−0.036**	−0.013	0.009	−0.131***
ICW	−0.026*	0.140***	0.125***	0.027*	0.089***	0.049***	−0.115***	−0.163***	−0.048***	−0.024	−0.093***
Future Downgrade	−0.046***	0.019	0.046***	−0.004	0.067***	−0.052***	0.113***	0.075***	0.011	0.005	0.129***
IT Spending	0.040**	−0.039**	−0.012	−0.002	0.010	0.027*	0.008	−0.020	0.027*	−0.020	−0.061***
Fortune	0.115***	−0.314***	−0.185***	−0.108***	−0.134***	−0.100***	0.286***	0.232***	0.007	0.107***	0.366***

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TABLE 3 (continued)

Panel B: Pearson Correlation Matrix for *Leverage* to *Fortune*

	Leverage	*MB*	*Profit-Avg*	*Profit-Vol*	*Tang-ibility*	*O-Score*	*Accr*	*S&P*	*Clean-AUOP*	*ICW*	*Future Down-grade*	*IT Spend-ing*	*For-tune*
Leverage	1												
MB	−0.064***	1											
ProfitAvg	−0.167***	0.597***	1										
ProfitVol	−0.058***	0.234***	0.127***	1									
Tangibility	0.202***	−0.177***	−0.068***	−0.100***	1								
O-Score	0.893***	−0.184***	−0.287***	−0.017	0.167***	1							
Accr	0.155***	0.159***	0.067***	0.216***	−0.001	0.140***	1						
S&P	0.061***	−0.014	−0.146***	0.255***	−0.175***	0.191***	0.152***	1					
CleanAUOP	−0.121***	0.096***	0.114***	0.036**	−0.061***	−0.098***	−0.017	0.009	1				
ICW	0.110***	−0.055***	−0.129***	0.063***	−0.075***	0.138***	0.096***	0.173***	−0.074***	1			
Future Downgrade	0.081***	−0.095***	−0.006	−0.037**	0.116***	0.095***	−0.029*	−0.268***	0.002	−0.007	1		
IT Spending	−0.039**	0.145***	0.109***	0.047***	−0.147***	−0.026*	0.011	0.056***	0.012	0.041***	−0.002	1	
Fortune	−0.065***	0.049***	0.092***	−0.087***	−0.008	−0.152***	−0.049***	−0.333***	−0.012	−0.080***	0.059***	−0.033**	1

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
All variables are defined in Appendix A.

TABLE 4

Effect of Borrower IT Reputation on Loan Contracting

Variables	(1) *Log AIS*	(2) *DSecu*	(3) *FinCovIdx*	(4) *GenCovIdx*
$IT\ Reputation_{it}$	−0.098***	−0.439***	−0.114**	−0.122*
	(−3.18)	(−3.31)	(−2.03)	(−1.78)
$Log\ Maturity_{ikt}$	0.050**	0.100*	0.011	−0.010
	(2.44)	(1.66)	(0.26)	(−0.28)
$Log\ Loan\ Size_{ikt}$	−0.093***			
	(−7.58)			
$Loan\ Concentration_{ikt}$		1.775***	0.350*	1.121***
		(4.68)	(1.90)	(7.41)
$Log\ NLenders_{ikt}$	−0.006	−0.067	0.122***	0.055*
	(−0.30)	(−1.36)	(4.84)	(1.67)
$Performance\ Pricing_{ikt}$	0.007	0.337***	0.846***	0.742***
	(0.29)	(4.88)	(16.36)	(20.88)
$Log\ NPriorDeals_{ikt}$	−0.048***	−0.055	−0.013	−0.004
	(−2.68)	(−1.11)	(−0.37)	(−0.15)
$Size_{it-1}$	−0.059**	−0.160**	−0.118***	−0.040
	(−2.07)	(−2.55)	(−5.15)	(−1.47)
$Leverage_{\ it-1}$	0.678***	1.474***	0.084	0.236
	(5.09)	(4.29)	(0.47)	(1.32)
MB_{it-1}	−0.097***	−0.141*	−0.031	−0.047
	(−3.26)	(−1.83)	(−0.98)	(−1.05)
$ProfitAvg_{it-1}$	−1.039***	−4.314***	−0.551	−0.895*
	(−4.07)	(−3.97)	(−1.34)	(−1.92)
$ProfitVol_{it-1}$	2.243***	6.797***	0.679	1.755**
	(4.44)	(4.37)	(1.16)	(2.19)
$Tangibility_{it-1}$	−0.032	−0.079	−0.268***	−0.111
	(−0.32)	(−0.24)	(−2.66)	(−0.88)
$O\text{-}Score_{it-1}$	0.014	0.039	0.038	0.038
	(0.70)	(0.72)	(1.45)	(1.47)
$Accr_{it-1}$	0.013	−0.064	−0.020	0.013
	(0.14)	(−0.16)	(−0.09)	(0.07)
$S\&P_{it-1}$	0.031***	0.029***	0.013***	0.008
	(7.00)	(2.80)	(4.34)	(1.54)
$CleanAUOP_{it-1}$	−0.020	−0.029	−0.009	−0.038
	(−0.90)	(−0.33)	(−0.29)	(−0.86)
ICW_{it-1}	0.119***	−0.015	0.039	0.125**
	(3.78)	(−0.15)	(0.53)	(2.47)
$Future\ Downgrade_{it-1}$	0.138***	0.204**	0.070	0.099*
	(3.68)	(2.26)	(1.38)	(1.90)
$IT\ Spending_{it-1}$	−0.337	−0.898	−1.565***	−0.831***
	(−0.64)	(−0.48)	(−3.36)	(−3.96)
MB_{it}	−0.037*	0.036	−0.092*	−0.086
	(−1.92)	(0.36)	(−1.68)	(−1.47)
$Profit_{it}$	−0.918**	−2.000**	0.585	0.096
	(−2.45)	(−2.18)	(1.23)	(0.27)
$Fortune_{it}$	−0.052	0.050	0.001	−0.016
	(−1.17)	(0.56)	(0.02)	(−0.32)
Term Spread	0.172***	0.008	0.089	0.089
	(3.01)	(0.08)	(1.60)	(1.54)
Credit Spread	0.153	0.131***	0.078*	0.029
	(1.25)	(2.75)	(1.78)	(0.71)
Constant	4.452***	−0.761	0.359	0.408
	(12.99)	(−0.63)	(0.68)	(0.79)

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TABLE 4 (continued)

Variables	(1) *Log AIS*	(2) *DSecu*	(3) *FinCovIdx*	(4) *GenCovIdx*
Loan Type Indicators	Included	Included	Included	Included
Loan Purpose Indicators	Included	Included	Included	Included
Year Indicators	Included	Included	Included	Included
Industry Indicators	Included	Included	Included	Included
No. of Observations	4,218	4,218	4,218	4,218
Adj./Pseudo R^2	0.72	0.37	0.18	0.23

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
This table presents the estimated results of the effect of borrowers' IT reputation on loan contracting terms. Column (1) is an ordinary least squares (OLS) regression, Column (2) is a Probit regression, and Columns (3) and (4) are Poisson regressions. The t-statistics (z-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering (Petersen 2009).
All variables are defined in Appendix A.

The Impact of IT Reputation on Future Credit Rating Downgrade and ICWs

To further support our proposition that IT reputation signals lower default risk, we test whether IT reputation reduces the occurrence of a borrower's future credit rating downgrade (H2a). To perform this test, we run a probit regression, with *Future Downgrade* being the dependent variable. The control variables include firm size (*Size*), leverage (*Leverage*), market-to-book ratio (*MB*), profitability (*Profit*), Ohlson's (1980) O-score (*O-Score*), current credit rating (*S&P*), IT spending (*IT Spending*), and corporate reputation (*Fortune*). Column (1) of Table 5 reports the results of this test. We find that the estimated coefficient on *IT Reputation* is significantly negative at the 1 percent level (–0.397, z = –3.14), consistent with H2a.

Next, we examine the link between IT reputation and information risk by testing whether a firm's IT reputation relates to the existence of ICWs. We estimate a probit model in which the dependent variable is *ICW*. We control for a series of known firm characteristics that have an impact on internal control effectiveness (Doyle, Ge, and McVay 2007).[8] In addition, we control for IT spending (*IT Spending*) and corporate reputation (*Fortune*). The sample size drops to 3,236 observations due to the data requirement on control variables. Column (2) of Table 5 reports the estimation results for the probit model. As shown in Column (2), the coefficient on *IT Reputation* is –0.369, significant at the 5 percent level, consistent with H2b. The results presented in Table 5 suggest that the effect of IT reputation on loan terms presented in Table 4 stems from both default and information risk, supporting our proposition.

VI. ADDITIONAL TESTS

Information Environment and the IT Reputation Effect

The impact of IT reputation on bank loan contracting may vary with the borrowers' information environment. Dispersion of analysts' earnings forecasts has been widely viewed as a proxy for investors' uncertainty about a firm's underlying performance (e.g., Imhoff and Lobo 1992; Barron, Kim, Lim, and Stevens 1998; Herrmann and Thomas 2005; Behn, Choi, and Kang. 2008; Byard, Li, and Yu 2011; Lee, Pandit, and Willis 2013). If IT reputation does play a role in reducing lenders' information risk, we expect its effect on loan contracting to be more pronounced when there is a higher level of uncertainty about borrower performance.

To empirically test this, we calculate analysts' forecast dispersion using analysts' earnings forecast data from I/B/E/S and then partition our sample into two subsamples of borrowing firms with high and low dispersions based on the annual median value of forecast dispersion. As earnings forecast data are not available for some observations, this additional test uses a reduced sample of 3,250 facility-years (1,620 in the low-dispersion subsample and 1,630 in the high-dispersion subsample). Table 6, Panel A presents the regression results for Equation (1) with two subsamples.[9]

As shown in Column (1) of Table 6, Panel A, when *Log AIS* is the dependent variable, the coefficient on *IT Reputation* is insignificant for the low-dispersion subsample (0.045, t = 0.78), while it is significantly negative at the 1 percent level for the

[8] These firm characteristics include firm size (*Size*), market-to-book ratio (*MB*), profitability (*Profit*), Ohlson's (1980) O-score (*O-Score*), credit rating (*S&P*), an indicator of mergers and acquisitions (*M&A*), an indicator of foreign transactions (*Foreign*), an indicator of restructures (*Restructure*), the natural log of the number of business segments (*Log NSeg*), growth rate in sales (*Sale Growth*), the natural log of firm age (*Log Age*), and the natural log of the number of special purpose entities (*Log NSPE*).

[9] For brevity, all analyses reported in this section report the coefficient on our test variable *IT Reputation* only.

TABLE 5

Effect of IT Reputation on Future Credit Rating Downgrade and Internal Control Weakness (ICW)

Variables	(1) *Future Downgrade* = 1	(2) *ICW* = 1
IT Reputation	−0.397***	−0.369**
	(−3.14)	(−2.35)
Size	−0.050	−0.174**
	(−0.91)	(−2.43)
Leverage	0.017	
	(0.07)	
MB	−0.212***	−0.154*
	(−2.63)	(−1.92)
Profit	−1.222	−3.222***
	(−1.37)	(−3.03)
O-Score	0.088**	0.080***
	(2.51)	(3.49)
S&P	−0.121***	0.038***
	(−8.23)	(3.92)
M&A		0.016
		(0.13)
Foreign		0.601***
		(4.12)
Restructure		0.231*
		(1.65)
Log NSeg		0.207
		(1.53)
Sale Growth		0.113
		(0.57)
Log FirmAge		0.418***
		(5.08)
Log NSPE		0.068
		(1.33)
IT Spending	0.195	1.880
	(0.21)	(0.68)
Fortune	−0.178**	−0.034
	(−2.05)	(−0.28)
Constant	3.568***	−7.781***
	(4.38)	(-11.45)
Year Indicators	Included	Included
Industry Indicators	Included	Included
No. of Observations	4,218	3,236
Adj./Pseudo R^2	0.18	0.36

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
This table presents the estimated results of the effect of a borrower's IT reputation on its default and information risk. Columns (1) and (2) are probit regressions. The dependent variable in Column (1) is an indicator variable that equals 1 if the borrower experiences a credit rating downgrade within the future three years, and 0 otherwise; and the dependent variable in Column (2) is an indicator variable that equals 1 if the borrower discloses any material control weakness in SEC filings (e.g., 10-K, 10-Q, 10KSB, 10QSB) under SOX 302, and 0 otherwise. The z-statistics, reported in parentheses, are based on standard errors clustered by firm.
All variables are defined in Appendix A.

high-dispersion subsample (−0.250, t = −3.44). The result of the t-test for the difference in estimated coefficients between the two subsamples shows that the difference is significant at the 1 percent level. The above results suggest that the effect of borrower IT reputation on the loan interest rate is more pronounced when analyst forecast dispersion is higher.

As shown in Column (2) of Table 6, Panel A, when the dependent variable is *DSecu,* the coefficient on *IT Reputation* is significant for both subsamples, but its magnitude is greater for the high-dispersion sample than for the low-dispersion sample.

TABLE 6

Effect of Borrower IT Reputation on Loan Contracting
Borrower Information Environment

Panel A: Dispersion of Analysts' Earnings Forecasts

Variable	(1) *Log AIS* Low Dispersion (I)	(1) *Log AIS* High Dispersion (II)	(2) *DSecu* Low Dispersion (I)	(2) *DSecu* High Dispersion (II)	(3) *FinCovIdx* Low Dispersion (I)	(3) *FinCovIdx* High Dispersion (II)	(4) *GenCovIdx* Low Dispersion (I)	(4) *GenCovIdx* High Dispersion (II)
Test Variable								
IT Reputation	0.045	−0.250***	−0.463**	−0.574***	−0.049	−0.113	−0.119	−0.184*
	(0.78)	(−3.44)	(−2.02)	(−3.43)	(−0.68)	(−1.18)	(−1.27)	(−1.75)
Diff.	−0.295***		−0.111		−0.064		−0.065	
(II) − (I)	(−2.98)		(−0.41)		(−0.55)		(−0.42)	
Loan- and borrower-specific characteristics, macroeconomic factors, loan purpose and industry indicators, and intercept are suppressed for brevity.								
n	1,620	1,630	1,620	1,630	1,620	1,630	1,620	1,630
Adj./Pseudo R^2	0.46	0.50	0.39	0.40	0.24	0.18	0.29	0.23

Panel B: Institutional Ownership

Variable	(1) *Log AIS* Low Inst. Ownership (I)	(1) *Log AIS* High Inst. Ownership (II)	(2) *DSecu* Low Inst. Ownership (I)	(2) *DSecu* High Inst. Ownership (II)	(3) *FinCovIdx* Low Inst. Ownership (I)	(3) *FinCovIdx* High Inst. Ownership (II)	(4) *GenCovIdx* Low Inst. Ownership (I)	(4) *GenCovIdx* High Inst. Ownership (II)
Test Variable								
IT Reputation	−0.138***	0.012	−1.103***	−0.174	−0.093	−0.023	−0.295***	−0.013
	(−3.05)	(0.22)	(−8.37)	(−0.61)	(−0.85)	(−0.24)	(−2.89)	(−0.19)
Diff.	0.150**		0.929**		0.070		0.282*	
(II) − (I)	(2.23)		(2.34)		(0.55)		(1.85)	
Loan- and borrower-specific characteristics, macroeconomic factors, loan purpose and industry indicators, and intercept are suppressed for brevity.								
n	1,445	1,450	1,445	1,450	1,445	1,450	1,445	1,450
Adj./Pseudo R^2	0.49	0.47	0.42	0.38	0.25	0.16	0.28	0.25

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
This table presents the regression results with the subsamples partitioned on the two borrower characteristics: dispersion of analysts' earnings forecast and ownership of institutional investors. The t-statistics (z-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering (Petersen 2009).
All variables are defined in Appendix A.

The result of the t-test reveals, however, that the difference in the estimated coefficients between the two subsamples is not significant. As shown in Column (3), when the dependent variable is *FinCovIdx,* the coefficient on *IT Reputation* is insignificant for both the low-dispersion and high-dispersion subsamples. As reported in Column (4), where *GenCovIdx* is used as the dependent variable, the estimated coefficient on *IT Reputation* is negative, but insignificant, for the low-dispersion subsample (−0.119, t = −1.27), while it is significantly negative for the high-dispersion subsample (−0.184, t = −1.75). However, the t-test result shows that the difference in the estimated coefficients on *IT Reputation* between the two subsamples is not significant at the conventional level.

Previous studies show that institutional investors play a role in improving stock price informativeness (e.g., Ayers and Freeman 2003; Ke and Petroni 2004; Piotroski and Roulstone 2004; Ke and Ramalingegowda 2005; Bushee and Goodman 2007). To the extent that institutional shareholdings improve the information environment facing a borrowing firm, we expect the favorable effect of IT reputation on loan contracting, if any, to be weaker (stronger) for borrowers with higher (lower) institutional shareholdings.

To empirically test our prediction, we obtain the institutional ownership data from the Thomson-Reuters Institutional Holdings (13F) Database. As the institutional ownership data are not available for some of our sample observations, we use 2,895 facility-years for this test. Based on the median value of the percentage of common shares of a borrowing firm held by institutional investors, we construct two subsamples of 1,445 and 1,450 facility-years with low and high institutional shareholdings, respectively. We estimate Equation (1) separately for the two subsamples and report the results in Panel B of Table 6.

As shown in Column (1) of Table 6, Panel B, when *Log AIS* is the dependent variable, the coefficient on *IT Reputation* is −0.138, significant at the 1 percent level, for the low institutional ownership subsample, while the coefficient is 0.012, insignificant at the conventional level, for the high institutional ownership subsample. The result of the t-test shows that the difference in the estimated coefficients between the two subsamples is significant at the 5 percent level. Consistent with our prediction, the results suggest that better information environments mitigate the effect of borrower IT reputation on the loan interest rate.

As shown in Column (2) of Table 6, Panel B, when *DSecu* is used as the dependent variable, the coefficient on *IT Reputation* is significantly negative at the 1 percent level for borrowers with low institutional shareholdings (−1.103, z = −8.37). In contrast, for borrowers with high institutional ownership, the association between *IT Reputation* and *DSecu* is negative, but insignificant (−0.174, z = −0.61). The result of the t-test shows that the difference in the estimated coefficients on *IT Reputation* between the two subsamples is significant at the 5 percent level. When *FinCovIdx* is used as the dependent variable (Column (3)), the coefficient on *IT Reputation* is insignificant for both subsamples. In contrast, when the dependent variable is *GenCovIdx* (Column (4)), the coefficient on *IT Reputation* is significantly negative at the 1 percent level for the low institutional ownership subsample, while the coefficient is insignificant for the high institutional ownership subsample. The result of the t-test indicates that the difference in the estimated coefficients between the two subsamples is significant at the 10 percent level.

Potential Endogeneity of IT Reputation

Several endogeneity-related issues might affect the validity of our results. Firms choose whether to signal their IT capability by voluntarily participating in the IW500 survey (self-selection). It is, therefore, likely that the same unobserved variables that motivate a firm's decision to signal its IT capability may be associated with the firm's credit risk (correlated omitted variables). Firms with more resources and better management are more likely to signal their IT capability and have lower credit risk. It is also possible that firms will be more inclined to project an IT capability signal when they are in need of borrowing (simultaneity bias). Such firms are more likely to seek external recognition and participate in the IW500 survey in order to signal their IT capability when they need to borrow.

Cognizant of these concerns, we select our sample (both treatment and control groups) from the population of firms that have appeared at least once in the IW500 list. Some of the potential bias introduced by self-selection and correlated omitted variables, we expect, would be mitigated by the fact that these sources of bias, if significant, are likely to affect both treatment and control group. If a firm chooses to signal its IT capability when it needs financing or in the year before seeking external financing (simultaneity bias), then the firm will be included in our control group. Therefore, if there is a simultaneity bias, then it will introduce a bias against finding a significant difference between the treatment and control samples. Note here that for a firm to be in the treatment group, it will have to signal its IT capability for five consecutive years, with the fifth year being the year of the loan.[10]

[10] However, we admit that this sample selection procedure limits the sample size and may restrict the generalizability of our findings.

Empirically, we use four different approaches to address the endogeneity issues. Our first approach is to use the Heckman (1979) procedure to control for endogeneity due to self-selection. Specifically, we first estimate the following probit model in Equation (2), in which the dependent variable is *IT Reputation* and the independent variables are potential determinants of the likelihood that a firm develops IT reputation (including industry and year indicators). Prior information system literature suggests that firms with a better financial position and more resources are more likely to have IT reputation (Staw and Epstein 2000; Lim et al. 2011). Thus, we include in the model a set of financial features that we have used in our main regressions (i.e., *Size, Leverage, MB, ProfitAvg, ProfitVol, Tangibility, O-Score,* and *S&P*). In addition, we include *IT Spending* and *Fortune* in the model since a firm's IT reputation is positively associated with its IT spending and corporate reputation. One may argue that a firm's financing need increases its incentive to be listed in the IW500 rankings and improve its IT reputation. We, thus, include in the model the amount of external financing (*Issue*). We formally specify:

$$\begin{aligned} Pr(IT\ Reputation_{it} = 1|X) = \Phi(&\beta_0 + \beta_1 Size_{it-1} + \beta_2 Leverage_{it-1} + \beta_3 MB_{it-1} + \beta_4 ProfitAvg_{it-1} + \beta_5 ProfitVol_{it-1} \\ &+ \beta_6 Tangibility_{it-1} + \beta_7 O\text{-}Score_{it-1} + \beta_8 \mathrm{S\&P}_{it-1} + \beta_9 IT\ Spending_{it-1} + \beta_{10} Fortune_{it} \\ &+ \beta_{11} Issue_{it} + \beta_{12} SITE_{it-1} + \beta_{13} Year\ Indicators + \beta_{14} Industry\ Indicators) \end{aligned} \tag{2}$$

We use the hierarchical power of a firm's IT executives (*SITE*) as an exclusionary variable (Lennox, Francis, and Wang 2012). Lim et al. (2013) theorize that IT executives will aim to achieve external legitimacy (i.e., build IT reputation by projecting IT capability signals), hoping that the top management team and board of directors will reciprocate by raising the IT executive's hierarchical power within the firm. This would motivate IT executives to project more signals in the future. Lim et al. (2013) document that firms that build such a culture of reciprocity are more likely to develop IT reputation. Given the institutional theory setting used by Lim et al. (2013),[11] we expect that stakeholders (such as banks) are more likely to focus on the signal rather than the driver behind the signal. While we expect that the hierarchical power of IT executives would be positively associated with IT reputation, we have no compelling reason to believe that it links to the firm's loan contracting terms. The variable *SITE* takes the value of 1 if the firm's senior IT executive has only the formal title of chief information officer (CIO), 2 if the executive has the title of CIO plus additional official title(s), and 0 otherwise.

Panel A of Table 7 presents the estimation results of the probit *IT Reputation* prediction model in Equation (2). The results in Panel A suggest that firms with higher volatility of profitability and lower credit ratings are less likely to develop IT reputation, while firms with higher corporate reputation are more likely to have IT reputation. Consistent with our prediction, we find in Panel A that the estimated coefficient on *SITE* is significantly positive, which suggests that firms with more powerful IT executives are more likely to develop IT reputation. To further check the validity of the exclusionary variable, we add *SITE* to Equation (1) as a control variable and estimate the regressions. The results, reported in Panel B of Table 7, show that although the estimated coefficients on *IT Reputation* remain significantly negative, *SITE* has an insignificant effect on loan spread, collateral requirement, or covenant indices. These results suggest that the hierarchical power of senior IT executives has no direct effect on loan contracting terms; thus, this factor can be excluded from the second-stage regressions of the Heckman (1979) procedure.

Next, we compute the inverse Mills ratio (IMR) from the first-stage probit model in Equation (2) and estimate our main regressions with *IMR* included as an additional control variable. Panel C of Table 7 reports the results of the second-stage regressions involving *IMR*. We find in Panel C that *IT Reputation* still has a significant impact on loan contracting terms after controlling for *IMR,* which is consistent with our main results. The coefficients on *IMR* are insignificant at the conventional level across all four columns. The above results suggest that potential endogeneity associated with borrowers' self-selection of IT reputation may not be a serious concern in our setting.[12]

Second, to more closely control for differences in treatment and control firms and to alleviate concerns about the functional form of the relationship, we construct a matched sample using the propensity score matching (PSM) method and reestimate our main regressions using the matched sample (e.g., Armstrong, Jagolinzer, and Larcker 2010; Lawrence, Minutti-Meza, and Zhang 2011). Specifically, we compute the predicted probability (i.e., propensity score) of IT reputation for all firms in our sample using the estimated coefficients of the probit *IT Reputation* prediction model in Equation (2). For each firm that has an IT reputation (i.e., treatment firm), we then choose a matched control firm that has the closest propensity score with the treatment firm, but has no IT reputation. We perform this one-to-one propensity score matching with the condition of common

[11] The institutional theory is grounded on: (1) the premise that internal and external stakeholders are the recipient of projected signals; and (2) the unobservable nature of the culture of reciprocity that develops over several years.

[12] The Variance Inflation Factors (VIFs) for *IT Reputation* and *IMR* are all lower than the conventional critical value of 10 in the second-stage regressions, indicating that multicollinearity is not a big problem when we implement the Heckman (1979) procedure (Belsley, Kuh, and Welsch 1980; Greene 2003).

TABLE 7

Heckman's (1979) Two-Step Procedure

Panel A: First-Step Probit Model

Variable	IT Reputation = 1
$Size_{it-1}$	−0.068
	(−1.05)
$Leverage_{it-1}$	0.326
	(0.82)
MB_{it-1}	0.075
	(0.72)
$ProfitAvg_{it-1}$	−1.163
	(−1.03)
$ProfitVol_{it-1}$	−3.399*
	(−1.75)
$Tangibility_{it-1}$	0.297
	(0.96)
$O\text{-}Score_{it-1}$	−0.075
	(−1.27)
$S\&P_{it-1}$	−0.027**
	(−2.23)
$ITSpending_{it-1}$	2.689
	(1.57)
$Issue_{it}$	0.155
	(0.52)
$Fortune_{it}$	0.330***
	(2.60)
$SITE_{it-1}$	0.152**
	(2.11)
Constant	−1.169*
	(−1.72)
Industry Indicators	Included
Year Indicators	Included
No. of Observations	1,617
Pseudo R^2	0.19

Panel B: Test of the Validity of the Exclusionary Variable (*SITE*)

Variables	(1) Log AIS	(2) DSecu	(3) FinCovIdx	(4) GenCovIdx
$IT\ Reputation_t$	−0.083*	−0.364**	−0.099*	−0.099
	(−1.94)	(−2.02)	(−1.68)	(−1.40)
$SITE_{t-1}$	0.001	0.017	0.012	0.021
	(0.03)	(0.35)	(0.52)	(0.86)
Control Variables	Included	Included	Included	Included
No. of Observations	2,448	2,448	2,448	2,448
Adj./Pseudo R^2	0.71	0.38	0.21	0.24

(continued on next page)

support and without replacement. After applying the above PSM procedures, we obtain a matched sample of 678 loan facilities: 339 facilities borrowed by treatment firms with IT reputation and 339 facilities borrowed by control firms without IT reputation.

Next, we check if our PSM procedure is effective in achieving covariate balance between the treatment and control samples. If we apply the PSM properly, then the treatment and control samples should appear similar along the dimensions included in Equation (2), with the exception of their IT reputation. Panel A of Table 8 reports the variable means and medians of the treatment and control samples, and tests of differences. As shown in Panel A, the two-sample t-test and Wilcoxon rank

TABLE 7 (continued)

Panel C: Second-Step Regressions with Inverse Mills Ratio (IMR)

Variables	(1) *Log AIS*	(2) *DSecu*	(3) *FinCovIdx*	(4) *GenCovIdx*
IT Reputation	−0.085**	−0.366**	−0.099*	−0.123
	(−1.98)	(−2.02)	(−1.76)	(−1.59)
IMR	−0.077	−0.350	−0.151	−0.338
	(−0.39)	(−0.80)	(−0.72)	(−1.31)
Control Variables	Included	Included	Included	Included
No. of Observations	2,448	2,448	2,448	2,448
Adj./Pseudo R^2	0.72	0.39	0.21	0.24

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
Panel A presents the results of the first-step probit model in which the dependent variable is *IT Reputation*. Panel B presents the results of the regressions of loan contracting terms on the test variable *IT Reputation* and the exclusionary variable, i.e., *SITE*, after including all control variables in the model. Panel C presents the results of the second-step regressions controlling for the Inverse Mills Ratio (*IMR*) from the first-step probit regression. In Panels B and C, Column (1) is an OLS regression, Column (2) is a Probit regression, and Columns (3) and (4) are Poisson regressions. The t-statistics (z-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering (Petersen 2009).
All variables are defined in Appendix A.

sum test indicate that the distributions of these firm characteristics between treatment and control firms are similar, indicating that our PSM procedure is successful. We then reestimate Equation (1) using this PSM sample. Panel B of Table 8 reports these estimation results. We find in Panel B that the coefficient on our test variable *IT Reputation* is significantly negative when the dependent variable is *Log AIS, DSecu, FinCovIdx,* or *GenCovIdx*.

Third, to address the endogeneity that relates to correlated, but unobservable, firm-specific factors, we use the firm fixed effects models to estimate the effect of IT reputation on loan contracting terms. The fixed effects research design controls for the unobservable differences between the treatment group (i.e., firms with IT reputation) and the control group (i.e., firms without IT reputation) and eliminates the potential bias caused by endogeneity as long as the unobservable factors remain constant during the sample period (Lennox et al. 2012). Because a firm's IT reputation develops over time, we believe that the unobservable sources of endogeneity tend to be innate, time-invariant, firm-specific characteristics. The results of firm fixed effects regressions are reported in Panel A of Table 9. We find in Panel A that the estimated coefficients on *IT Reputation* are significantly negative when *Log AIS* or *DSecu* is the dependent variable, which is consistent with our main results. To the extent that firm fixed effects capture the unobservable, time-invariant, firm-specific factors that potentially affect loan terms, these results help us alleviate the concern about the correlated omitted variables. However, Columns (3) and (4) of Panel A do not show significant impact of a borrower's IT reputation on covenants when we estimate firm fixed effects regressions.

Finally, to further address concerns about the correlated omitted variables and reverse causality (Bradshaw, Bushee, and Miller 2004), we conduct a changes analysis to examine the effect of the change in a borrower's IT reputation on the changes in loan terms. Panel B of Table 9 reports these results. We find in Panel B that the change in IT reputation is significantly and negatively associated with the change in loan spread, although the change in IT reputation seems to have no significant impact on the changes in covenants and collateral requirements. In summary, the results based on the Heckman (1979) procedure, the PSM approach, firm fixed effects regressions, and changes regressions demonstrate the robustness of our results and help alleviate concerns about potential endogeneity.

Analysis of Firms with IT Reputation

We perform an additional test by analyzing a reduced sample of 148 firms that have attained IT reputation for at least one year during our sample period. These 148 firms have 931 loan facilities in our sample. We estimate our regression models with this reduced sample by controlling for firm fixed effects. In so doing, we exploit the effect of the overtime variation in IT reputation on loan terms for this group of firms. Panel C of Table 9 reports these results. For this small sample of loans, we still find that IT reputation is associated with a lower loan spread, a lower likelihood of collateral requirement, and fewer general covenants. These results further mitigate the concern about self-selection bias and corroborate our main findings.

VII. CONCLUDING REMARKS

This study examines whether and how borrowers' IT reputation affects both price and non-price terms of bank loan contracting using 4,218 bank loan facilities and the IW500 list of America's most IT-innovative firms. Our results show that

TABLE 8

Propensity Score Matching (PSM) Approach

Panel A: Covariate Balance between Treatment and Control Samples

	IT Reputation = 0 (n = 339)		IT Reputation = 1 (n = 339)		Test of Difference	
Variables	**Mean**	**Median**	**Mean**	**Median**	**t**	**z**
Size	8.890	8.971	8.921	8.865	−0.31	−0.18
Leverage	0.639	0.632	0.648	0.629	−0.43	0.50
MB	1.973	1.651	1.884	1.592	1.10	−0.06
ProfitAvg	0.155	0.144	0.154	0.151	0.21	−0.06
ProfitVol	0.027	0.020	0.026	0.021	0.67	0.70
Tangibility	0.336	0.284	0.345	0.299	−0.55	−0.18
O-Score	−7.459	−7.547	−7.380	−7.390	−0.56	−0.04
S&P	9.233	8.000	9.422	9.000	−0.48	−0.53
IT Spending	0.028	0.021	0.029	0.021	−0.42	−0.42
Fortune	0.575	1.000	0.587	1.000	−0.31	−0.31
Issue	0.008	−0.005	0.012	−0.005	−0.42	−0.73
SITE	1.463	2.000	1.563	2.000	−1.63	−1.15

Panel B: Regressions with PSM Sample

Variables	**(1) *Log AIS***	**(2) *DSecu***	**(3) *FinCovIdx***	**(4) *GenCovIdx***
IT Reputation	−0.098**	−0.570**	−0.110**	−0.159*
	(−2.02)	(−2.07)	(−2.35)	(−1.81)
Control Variables	Included	Included	Included	Included
No. of Observations	678	678	678	678
Adj./Pseudo R^2	0.68	0.48	0.25	0.30

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
Propensity score is the predicted probability estimated from the probit model in Panel A. Each borrower with IT reputation (i.e., treatment firm) is matched with a borrower without IT reputation (i.e., control firm) with the closest propensity score. This procedure results in 678 loan facilities, which consist of 339 borrowed by treatment firms and 339 borrowed by control firms. Panel A of Table 8 presents the covariate means and medians of the treatment and control sample, and tests of differences. Panel B presents the regression results with the PSM sample. Column (1) is an OLS regression, Column (2) is a Probit regression, and Columns (3) and (4) are Poisson regressions. The t-statistics (z-statistics), in parentheses, are based on standard errors corrected for heteroscedasticity and firm- and year-level (two-dimensional) clustering (Petersen 2009).
All variables are defined in Appendix A.

banks and other private lenders value borrowers' IT reputation, and that firms with IT reputation enjoy lower interest rates and more favorable non-price loan terms (lower collateral requirement and fewer restrictive covenants) compared to those without it. Exploring the channels through which IT reputation plays a role in loan contracting, our analysis shows that borrowers with IT reputation have lower default and information risks. These findings contribute to bank loan and IT business value literatures.

Our results have important implications for both lenders and borrowers. Even though banks have access to inside information about borrowing firms, they can benefit from the processing of public IT capability signals because IT reputation can help them mitigate information opaqueness or uncertainty about borrowers. Given that the IT capability is unobservable, IT reputations enable lenders to reward firms that generate consecutive and consistent signals about their IT capability. Consequently, senior management of IT-capable firms, including CFOs, have an incentive to continue signaling their firm's IT capability credibly to mitigate the information asymmetry and help shape the beliefs of interested stakeholders: the expected payoffs are significant both statistically and economically.

Finally, we admit that like most other studies, ours has its limitations, and these limitations contain the seeds for future research. For example, our study is biased toward a sample of large firms due to the coverage of the IW500 and the DealScan database. Future research might examine whether our findings apply also to small firms. In addition, researchers may want to explore whether a firm's image on social media matters to its financing activities.

TABLE 9

Additional Tests

Panel A: Firm Fixed Effects Regressions

Variables	(1) *Log AIS*	(2) *DSecu*	(3) *FinCovIdx*	(4) *GenCovIdx*
IT Reputation$_{it}$	−0.078**	−0.718**	−0.011	−0.072
	(−2.32)	(−2.20)	(−0.15)	(−1.24)
Control Variables	Included	Included	Included	Included
No. of Observations	4,218	4,218	4,218	4,218
R^2/Pseudo R^2	0.37	0.22		
Chi-squared		357.66	740.60	1,462.01
(p-value)		(0.00)	(0.00)	(0.00)

This panel presents the firm fixed effects regression results of the effect of borrowers' IT reputation on loan contracting terms. Column (1) is a firm fixed effects linear regression, Column (2) is a firm fixed effects logistic regression, and Columns (3)–(4) are firm fixed effects Poisson regressions.

Panel B: Changes Regressions

Variables	(1) *ΔLog AIS*	(2) *ΔDSecu*	(3) *ΔFinCovIdx*	(4) *ΔGenCovIdx*
ΔIT Reputation$_{it}$	−0.054**	−0.064	0.024	−0.181
	(−1.98)	(−0.28)	(0.15)	(−1.34)
Control Variables	Included	Included	Included	Included
No. of Observations	2,060	2,060	2,060	2,060
Adj. R^2/Pseudo R^2	0.51	0.11	0.14	0.11

This panel presents the changes regression results of the effect of borrowers' IT reputation on loan contracting terms. Column (1) is an OLS regression, and Columns (2)–(4) are ordered logit regressions.

Panel C: Firm Fixed Effects Regressions with 148 Firms with IT Reputation

Variables	(1) *Log AIS*	(2) *DSecu*	(3) *FinCovIdx*	(4) *GenCovIdx*
IT Reputation$_{it}$	−0.089**	−4.846***	−0.044	−0.123*
	(−2.56)	(−3.79)	(−0.52)	(−1.86)
Control Variables	Included	Included	Included	Included
No. of Observations	931	931	931	931
R^2/Pseudo R^2	0.50	0.64		
Chi-squared		194.50	182.74	445.32
(p-value)		(0.00)	(0.00)	(0.00)

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, in a two-tailed test.
This panel presents the results of within-firm analysis with 931 loans borrowed by 148 firms that have sustained IT reputation for at least one year during our sample period. Column (1) is a firm fixed effects linear regression, Column (2) is a firm fixed effects logistic regression, and Columns (3)–(4) are firm fixed effects Poisson regressions.
All variables are defined in Appendix A.

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APPENDIX A

Variable Definitions

Variable	Definition
IT Reputation Variable	
IT Reputation	An indicator variable that equals 1 if the borrower is recognized in IW500 for five consecutive years (i.e., the year when the loan is initiated and the previous four years), and 0 otherwise.
Dependent 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*.
DSecu	An indicator variable that equals 1 if the loan is secured with collateral, and 0 otherwise.
FinCovIdx	Financial covenant index, constructed by counting the number of financial covenants included in a loan contract.
GenCovIdx	General covenant index, constructed by counting the number of general covenants included in a loan contract.
Loan-Specific Control Variables	
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* plus the borrower's total liabilities.
NLenders	Number of lenders in the loan deal.
Log NLenders	The natural log of *NLenders*.
Performance Pricing	An indicator variable that equals 1 if the loan contract includes performance pricing provisions, and 0 otherwise.
NPriorDeals	Number of previous loan deals between a borrower and the lead arrangers for the current deal during the past five years.
Log NPriorDeals	The natural log of 1 plus *NPriorDeals*.
Loan Type Indicators	Indicator variables for the types of loan facilities in DealScan, including term loan, revolver, and 364-day facility.
Loan Purpose Indicators	Indicator variables for the purposes of loan facilities in DealScan, including corporate purposes, debt repayment, working capital, CP backup, takeover, acquisition line, and leverage buyout offers.
Macroeconomic Variables	
Term Spread	Difference in the yield between ten- 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 the yield between BAA- and AAA-rated corporate bonds measured one month before the loan becomes active, obtained from the Federal Reserve Board of Governors.
Borrower-Specific Control Variables	
Size	Firm size, which is the natural log of total assets in millions of dollars.
Leverage	Leverage ratio, defined as total 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.
Profit	EBITDA divided by average total assets.
ProfitAvg	Average *Profit* over the past five years.
ProfitVol	Standard deviation of *Profit* over the past five years.
Tangibility	Net PP&E divided by total assets.
O-Score	Ohlson's (1980) O-score; larger *O-Score* implies higher default risk.
Accr	The absolute value of abnormal accruals obtained from the modified Jones model (Dechow, Sloan, and Sweeney 1995) considering accounting conservatism (Ball and Shivakumar 2006).
S&P	Numerical value of S&P Domestic Long-Term Issuer Credit Rating. AAA = 1, AA+ = 2, AA = 3,...,D = 21, SD = 22, NR = 23.
CleanAUOP	An indicator variable that equals 1 if the auditor issues an unqualified opinion without explanatory language, and 0 otherwise.
ICW	An indicator variable that equals 1 if the borrower discloses any material control weakness in Securities and Exchange Commission (SEC) filings (e.g., 10-K, 10-Q, 10KSB, 10QSB) under SOX 302, and 0 otherwise.

(continued on next page)

APPENDIX A (continued)

Variable	Definition
Future Downgrade	An indicator variable that equals 1 if the borrower experiences a credit rating downgrade within the future three years, and 0 otherwise.
IT Spending	Firm-level IT expenditures as a percentage of sales, which is based on survey results from the IW500. We replace missing values by the corresponding industry average IT spending reported in IW500 for that year.
Fortune	An indicator variable that equals 1 if the borrower is one of *Fortune's* Most Admired companies in the specific year, and 0 otherwise.
M&A	An indicator variable that equals 1 if the firm is involved in mergers or acquisitions, and 0 otherwise.
Foreign	An indicator variable that equals 1 if the firm has a nonzero foreign currency translation, and 0 otherwise.
Restructure	An indicator variable that equals 1 if any of Compustat data items related to restructuring costs (RCP, RCA, RCEPS, and RCD) are nonzero, and 0 otherwise.
NSeg	The number of business segments.
Log NSeg	The natural log of *NSeg*.
Sale Growth	Growth rate in sales.
FirmAge	The number of years the firm has data in Compustat.
Log FirmAge	The natural log of *FirmAge*.
NSPE	The number of special purpose entities (SPEs) used by the firm.
Log NSPE	The natural log of 1 plus *NSPE*.
Issue	The amount of net issuance of stock and long-term debt divided by average total assets.
SITE	Hierarchical power of IT executives. *SITE* takes the value of 1 if the firm's senior IT executive has just the formal title of CIO, 2 if the executive has the title of CIO plus additional official title(s), and 0 otherwise.