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The Effect of Organization Capital on the Cost of Bank Loans

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Abstract

We find that organization capital is negatively related to the cost of bank loans. This finding is robust to additional analyses including those that address omitted variable bias and reverse causality. In addition, we find that organization capital reduces all-in-spread-undrawn. When we decompose the bank loan cost, we find that organization capital increases facility fees due to its risk-engendering characteristics. Finally, we find that organization capital is positively associated with a high likelihood of the presence of inventors and innovation output, consistent with the argument that organization capital is embedded in the key talent within a firm.

I. Introduction

Organization capital is "the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products" (Evenson and Westphal (1995), p. 2237). It consists of four elements: human capital,[1] values and norms,[2] knowledge and expertise,[3] and processes and

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[1]For example, what Steve Jobs is to Apple, Inc. is an illustration of the human capital element of organization capital.

[2]For example, Eastman Kodak Company did not possess visionary values when its employee, Steven Sasson, invented the first digital camera within the company in 1975. Instead, Kodak tried to suppress the new invention to protect its profitable film department, which resulted in its bankruptcy in Jan. 2012.

[3]For example, John Bogle founded Vanguard based on his knowledge, accumulated from his undergraduate thesis finding that most mutual funds at that time did not make more money than simple investment in the S&P 500 index, as well as further research.

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practices (Lev, Radhakrishnan, and Evans (2016)).[4] Thus, organization capital is partly firm-specific and partly embedded in firms' key talent, and consequently is shared between firms and their key talent (Eisfeldt and Papanikolaou (2013), Li, Qiu, and Shen (2018)). The literature shows that organization capital is an important intangible resource for firms and is growing in importance (Corrado, Hulten, and Sichel (2009), Eisfeldt and Papanikolaou (2014), Lev et al. (2016), and Falato, Kadyrzhanova, Sim, and Steri (2022)). For instance, Corrado et al. (2009) report that, since the 1960s, intangible capital has more than tripled, reaching \$3.6 trillion by the early 2000s, of which organization capital accounts for about 30%, making it the single largest category of such capital.[5] Similarly, Falato et al. (2022) point out that by 2010, intangible capital relative to book assets had increased by 90% since the 1970s, with organizational capital being the biggest component of this increase.

Given its importance, prior studies provide evidence of a positive relationship between organization capital and firms' stock price performance (e.g., Lev, Radhakrishnan, and Zhang (2009), Eisfeldt and Papanikolaou (2013)). In this article, we add to this literature by examining whether debtholders value organization capital by exploring the relationship between firms' organization capital and their cost of bank loans. The bank loan market has been the largest source of external corporate capital both globally and in the United States for at least a decade. For instance, in 2015, the global syndicated loan volume was \$4.7 trillion with the U.S. portion being \$2.2 trillion, more than the combined issuance of corporate bonds (\$1.5 trillion) and IPOs totaling \$188.4 billion).[6] Thus, to the extent that organization capital is priced in the bank loan market, it should have a material impact on firms' marginal cost of capital, and hence their capital market decisions.

Although most organization capital, according to accounting regulations, is an internally generated intangible asset and is not recognized on the balance sheet, banks generally analyze both accounting and nonaccounting information when evaluating the creditworthiness of the borrower. Among nonaccounting information, lenders oftentimes mention the value of those unrecognized intangible assets in generating future cash flows, which is a primary consideration when evaluating the credit risk of borrowers. For example, in their survey, Donelson, Jennings, and Mcinnis (2017) find that commercial lenders consider "character, reputation, and experience of management" as the third most important factor, which is more important than firm fundamentals such as liquidity and profitability, when making lending decisions. Likewise, an Athena Alliance article states that "the bank uses intangibles as another factor in the credit rating," and "the traditional credit rating

[4]For example, Uber and Airbnb built their platforms to enable assets not owned by them to be productive (Lev et al. (2016)).

[5]In addition, as pointed out by Eisfeldt and Papanikolaou (2014), organization capital has played an increasingly important role as a factor of production over the past 2 decades and continues to do so. For instance, between 1975 and 2012, organization capital grew by 2% per year relative to physical capital, and by 1993 it was 19% higher than in 1975.

[6]See Thomson Reuters for data on syndicated loans and equity (https://www.hitc.com/en-gb/2016/01/04/syndicated-loans-review-full-year-2015-thomson-reuters/, https://www.hitc.com/en-gb/2016/01/04/equity-capital-markets-review-full-year-2015-thomson-reuters/) and the Securities Industry and Financial Markets Association (SIFMA; https://www.sifma.org/wp-content/uploads/2017/05/2015-year-in-review.pdf) for data on bond issuance. See also Sufi (2007) and Ivashina (2009).

process subsumes intangibles, such as the quality of management, indirectly into the analysis" (Ellis (2009)). A recent *Forbes* article explicitly points out that lenders develop corporate credit frameworks that include an analysis of operational risk, which is the potential financial loss at a company or organization that can happen due to problems with people, processes, technology, and external events (https://www.forbes.com/sites/mayrarodriguezvalladares/2020/08/01/credit-analysis-frameworks-should-be-changed-to-incorporate-covid-19-uncertainties-and-risks/?sh=2aedcf825281). In Appendix A, we provide anecdotal evidence to illustrate how each of the four main components of organization capital (i.e., human capital, values and norms, knowledge and expertise, and processes and practices) affects credit ratings by credit analysts.

In addition, we interviewed the managing director and group head of leveraged lending at BMO Capital Markets, who indicated that borrowers' intangibles like organization capital are factored into their credit evaluation mainly through two channels: credit analysis and enterprise value. For credit analysis, the senior manager pointed out that his division would calculate a credit rating of a borrower using a proprietary probability of default model based on the cash flow principle. He further pointed out that key-talent risk, for example, Steve Jobs to Apple, is an important component of credit analysis. For enterprise value, the senior manager mentioned that they rely on discounted cash flow models and evaluate how intangibles, like corporate culture and management system and processes, affect future cash flows. In sum, our interview confirms that intangibles are one of the important parameters that go into loan pricing.

Although existing evidence documents a positive relation between organization capital and stock price performance (e.g., Eisfeldt and Papanikolaou (2013)), its effect on the cost of bank loans is ambiguous because it is potentially value-enhancing and risk-engendering (e.g., Lev et al. (2009), Eisfeldt and Papanikolaou (2013)). This is the case because, unlike other forms of intangible capital, organization capital is comprised of two components, one that is firm-specific and the other that is represented by important labor inputs, such as managers, scientists, engineers, and the firm's sales force, among others (Atkeson and Kehoe (2002), Lev and Radhakrishnan (2005), and Eisfeldt and Papanikolaou (2013)). Eisfeldt and Papanikolaou (2013) point out that, unlike physical capital, to which shareholders own all the cash flow rights, key talent also shares in the cash flow rights to investment in organization capital in firms. Given the risk of key talent leaving firms if the value of outside options is greater than the value of staying, the cash flow rights related to key talent could fluctuate, thereby increasing the volatility of cash flows and hence the firm's risk. Thus, these two characteristics of organization capital (i.e., value-enhancing and risk-engendering) would lead to two opposing predictions regarding the relation between organization capital and the cost of bank loans.

Using a sample of 29,221 loan facilities from 1982 to 2019, we find that organization capital is negatively associated with bank loan spreads, with the relationship being economically meaningful. Specifically, we find that a 1-standard-deviation increase in organization capital is associated with a 2.4% decrease in loan spreads. Given that the mean value of loan spreads in our sample is 194 basis points, this 2.4% decrease in loan spreads indicates a 4.7 basis points decrease for an average firm. We also use seven alternative measures of organization capital

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and find consistent results.[7] Specifically, we find that a 1-standard-deviation increase in alternative measures of organization capital result in an increase in economic significance ranging from a decrease of 3.3 to 11.6 basis points in loan spreads. This finding suggests that it is the value-enhancing aspect of organization capital, rather than its risk-engendering characteristic, that dominates the relation between organization capital and the cost of bank loans.

One could argue that our organization capital measure simply captures innovation. To mitigate this concern, we regress organization capital on innovative capacity, and use the residual as an alternative measure of organization capital. The regression result using this alternative measure as the independent variable is consistent with our baseline result.[8]

To mitigate endogeneity concerns, we implement three sets of tests. First, to mitigate omitted variable bias concerns, we follow Li et al. (2018) and use state-level unemployment insurance benefits as an instrumental variable and conduct a 2-stage least squares estimation. Losing talent is the key risk for firms that invest in organizaiton capital (Eisfeldt and Papanikolaou (2013)). Prior studies have documented a positive association between unemployment insurance benefits and employees' investment in marketable human capital, and a negative association between unemployment insurance benefits and job switches (Levhari and Weiss (1974), Brown and Kaufold (1988), Light and Omori (2004), and Hassler, Rodriguez Mora, Storesletten, and Zilibotti (2005)). Thus, unemployment insurance benefits provide firms with strong incentives to invest in organization capital.[9] Therefore, we expect and find that firms in states with more generous unemployment insurance benefits invest more in organization capital than firms in states with less generous benefits. After instrumenting organization capital, we continue to find a negative and significant effect on loan spreads.

Second, to provide additional evidence on a causal relationship between organization capital and bank loan pricing, we utilize the staggered recognition of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts as a quasi-natural experiment. IDD is a legal doctrine stating that a firm's former employees can be prevented from working at a rival company if doing so would inevitably disclose the firm's trade secrets to its rival (Hamler (2000)). This serves to protect firms' competitive edge and as such, encourages investment in organization capital.[10] We find that firms invest more in organization capital after the state courts recognize IDD, confirming the validity of our assumption. We further find that firms located in

[7]We use a relatively large number of alternative measures of organization capital given the ongoing debate as to the appropriate measure.

[8]We also use innovative capacity as an additional control variable in our baseline regression and find consistent results.

[9]Given that we find a positive association between organization capital and state-level unemployment insurance benefits, this provides supportive evidence that organization capital is embedded in employees, and that organization-capital-engendered risk partly results from the possibility of employees leaving, consistent with the definition of organization capital used in this article.

[10]We find that firms have higher organization capital after the state courts recognize IDD compared to firms in those states before the courts recognize IDD, and compared to firms in states that have never recognized IDD. This indicates that one of the risks resulting from organization capital is the possibility of employees leaving for rival firms and revealing corporate secrets, consistent with the definition of organization capital used in this article.

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IDD-adopting states enjoy lower loan spreads after IDD adoptions, suggesting a causal effect of organization capital on the costs of bank loans.

Third, to mitigate the problem of functional form misspecification on the relationship between organization capital and bank loan spreads, following Francis, Mani, Sharma, and Wu (2021), we employ a propensity score matching method by matching high-organization-capital firms with low-organization-capital firms. That is, both the treatment group (i.e., high-organization-capital firms) and the control group (i.e., low-organization-capital firms) have the same firm characteristics except for the level of organization capital. We continue to find a significantly negative relation between organization capital and loan spreads after using the matched sample. In sum, our three sets of tests using different econometrics methods all suggest that the relation between organization capital and the cost of bank loans is likely to be causal.

Berg, Saunders, and Steffen (2016) point out that, along with the spread, the accompanying fees associated with bank loans are important components of the total cost of bank loans to firms. To examine whether organization capital impacts the other components of the cost of bank loans, we regress the total cost of borrowing (which accounts for the different fees associated with bank loans) on organization capital. For completeness, we also examine the impact of organization capital on the all-in-spread-undrawn (AISU), defined as commitment fee plus facility fee. We find that organization capital negatively affects both the total cost of borrowing and the AISU.

Next, we separately examine the impact of organization capital on the two components of AISU and find that organization capital is positively associated with facility fees, but negatively associated with commitment fees. Fees are the prices of options embedded in the loan contracts and, as such, transfer value from lenders to borrowers with a credit line, and are higher for high-volatility firms (Berg et al. (2016)). The positive association between organization capital and facility fees is consistent with the risk-engendering characteristics of organization capital. Combined with the results of loan spread, this indicates that banks recognize both value-contributing and risk-engendering characteristics of organization capital. These results indicate that, although banks account for the risk-increasing aspect of organization capital through facility fees, the value-enhancing characteristic dominates the relation between organization capital and the total cost of borrowing. Berg et al. (2016) argue that banks also use fees to screen borrowers, and that borrowers can signal a lower use of credit lines by selecting lower commitment fees. This could explain the negative association between organization capital and commitment fees. In addition, we find supportive evidence that firms with high organization capital have lower usage of credit lines 3 years after loan origination.

As mentioned above, a significant feature of organization capital is the embeddedness of key talent. Consequently, we test whether key talent is an underlying channel through which organization capital affects the cost of borrowing. It is possible that banks may recognize that organization capital embedded in key talent influences the borrower's innovation (Francis et al. (2021)) and operating performance, and factor this effect in when setting loan prices. To provide evidence as to whether this is the case, we examine the relationship between organization capital and the presence of inventors, as well as innovation outputs. We find that

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organization capital is positively associated with the presence of inventors and innovation output.

Our article contributes to both the organization capital and bank loans literature. First, our article complements the literature on the valuation effect of organization capital. Prior studies (e.g., Lev and Radhakrishnan (2005), Lev et al. (2009), and Eisfeldt and Papanikolaou (2013)) focus on the impact of organization capital on the stock market and provide little evidence on whether the superior stock price performance of firms with high organization capital results from mispricing due to lack of information on organization capital (Lev et al. (2009)) or inappropriate risk adjustment (Eisfeldt and Papanikolaou (2013)). That is, it is not clear whether value-contributing or risk-engendering characteristics of organization capital dominate in the case of high stock returns for firms with high organization capital, because both lead to the same prediction. We study the impact of organization capital on another major source of capital for firms, bank loans. These two characteristics of organization capital predict two opposing effects on the cost of bank loans. We find that organization capital reduces the loan spread as well as the total cost of borrowing and increases facility fees, indicating that banks value the value-enhancing characteristic of organization capital more than they are concerned with its risk-increasing characteristic, even though they recognize the risk-increasing aspect of high organization capital.

Second, our article contributes to the literature on bank loans. As pointed out by Peters and Taylor ((2017), p. 251), "the US economy has shifted toward service- and technology-based industries, which has made intangible assets such as human capital, innovative products, brands, patents, software, customer relationships, databases, and distribution systems increasingly important." Our results show the importance of intangibles in shaping firms' cost of capital.

Finally, our article also directly answers Berg et al.'s (2016) call for the study of bank loans using their complex pricing structure, rather than the interest spread alone. We provide supportive evidence for Berg et al.'s (2016) argument that fees (e.g., facility fees) are prices for options embedded in loan contracts and are higher for volatile firms, and that borrowers signal a lower use of bank loans by selecting a lower commitment fee.

II. Related Literature and Hypotheses Development

There is no consensus on the definition of organization capital. Some researchers view organization capital as embedded in employees (e.g., Prescott and Visscher (1980), Eisfeldt and Papanikolaou (2013)), while others view it as firm-specific and embedded in the organization itself (e.g., Atkeson and Kehoe (2002), Lev and Radhakrishnan (2005)). In this article, as pointed out in the introduction, we adopt Evenson and Westphal's ((1995), p. 2237) definition of organization capital as "the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products."[11]

[11]Note that this definition builds on the seminal work of Prescott and Visscher (1980) that views the enterprise as an agglomeration of employees and that information within the firm about its employees is organization capital.

Thus, organization capital is partly firm-specific and partly embedded in employees (Eisfeldt and Papanikolaou (2013)).

Prior studies have linked organization capital to operating performance and stock returns. Organization capital increases operational efficiency by facilitating the match between human skills and physical production. Due to its proprietary nature, organization capital cannot be imitated easily by competitors (Prescott and Visscher (1980)), which creates competitive edges for firms. Consistent with this argument, Lev et al. (2009) report that organization capital is positively associated with firms' future operating performance and abnormal stock returns. They attribute the abnormal stock returns to mispricing due to a lack of information on organization capital, rather than inappropriate risk adjustment. In support of their argument, Lev and Radhakrishnan (2005) document that financial analysts, important information intermediaries in stock markets, fail to fully evaluate the value of firms' organization capital. Li et al. (2018), building on the work of Lev et al. (2009), study the role of organization capital in the merger and acquisition (M&A) setting and find that firms with high levels of organization capital achieve better operating and stock performance after acquisitions.

However, Eisfeldt and Papanikolaou (2013) contend that the superior stock performance of firms with high organization capital is a risk premium required by shareholders for the additional risk taken when they invest in those firms. They argue that organization capital is embedded in firms' key talent, shared between the firms and their key talent, and potentially transferable from one organization to another through labor mobility, making it riskier than physical capital from the firm's shareholders' perspective. Boguth, Newton, and Simutin (2021), building on the work of Eisfeldt and Papanikolaou (2013), find that the fragility of organization capital, proxied by the size of the firm's top management team, also matters in the stock market. They find that firms with smaller top management teams are characterized by higher risk levels, which they attribute to the fact that the organization capital in these firms is concentrated in a smaller number of key talent.

As pointed out above, the evidence indicates that the firm's equity return is increasing in its organization capital because shareholders require a higher risk premium. However, whether the firm's cost of debt capital is increasing in its organization capital is unclear. Understanding whether this is the case is important given that bank loans serve as one of the most important financial resources for firms (Bharath, Sunder, and Sunder (2008), Hasan, Hoi, Wu, and Zhang (2014)). Further, the cost of bank loans is one of the important factors that determine firm value. Given the fact that organization capital is value-contributing but also risk-engendering, the impact of organization capital on the cost of borrowing is not straightforward. Thus, we propose two competing arguments.

We pointed out above that organization capital could benefit firms by improving operating performance (Lev et al. (2009)). Eisfeldt and Papanikolaou (2013) also document that organization capital increases the productivity of a firm, and therefore firm performance, resulting in firms earning higher returns. In addition, Li et al. (2018) document that firms with higher organization capital perform better in terms of operations and stock returns after M&As. The improved firm performance associated with firms characterized by relatively higher levels of organization capital increases future cash flows, which reduces such firms' default risk,

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suggesting that banks may require lower interest rates, all else being equal. We, therefore, predict the following:

Hypothesis 1a. Firms with higher organization capital have a lower cost of bank loans.

However, Eisfeldt and Papanikolaou (2013) argue that organization capital is embedded in firms' key talent and shared between firms and their key talent, and is, therefore, riskier than physical capital. It should be noted that, along with increasing the riskiness of firms' cash flows, organization capital is intangible and unlikely to be used as collateral. This suggests that banks are likely to require higher interest rates on loans for firms with high levels of organization capital.

In addition, banks are exposed to the possibility of risk shifting by firms subsequent to the loans being made. If banks expect firms to invest in more tangible capital after receiving the loan, banks will charge interest rates and fees reflecting the risks. However, if firms were to invest in intangible capital such as organization capital after receiving the loan, the risk would shift to the banks, because the interest rate and fees charged would not cover this additional risk. To the extent that banks believe that firms with a significant amount of organization capital are likely to continue investing in organization capital, banks will be wary of the distinct possibility of risk shifting once the loan contract terms have been finalized. This suggests that banks are likely to demand higher interest rates for firms characterized by relatively high levels of organization capital. We, therefore, make the following prediction:

Hypothesis 1b. Firms with higher organization capital have a higher cost of bank loans.

III. Data and Measurement

A. Sample

We obtain bank loan data from the Dealscan database provided by the Loan Pricing Corporation. The Dealscan database provides price and nonprice information on bank loans. We merge these data with data from Compustat to obtain the requisite accounting data. Our data cover firms with bank loans issued during the period of 1982 to 2019. The sample is from 1982 because this is the first year with bank loan observations after merging Dealscan database with Compustat. Within our sample, several firms have multiple loan packages or deals in the same year. Because loan characteristics vary across packages and deals, following prior studies (e.g., Bharath et al. (2008), Hasan et al. (2014)), we treat each loan as a separate sample observation. The final sample contains 29,221 loans for 4,296 unique firms.

B. Organization Capital

Eisfeldt and Papanikolaou (2013) propose a measure for organization capital and cross-validate the organization capital measure with the likelihood of "loss of key personnel" being listed as a risk factor in firms' 10-K filings, managerial quality

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scores from Bloom and Van Reenen (2007), IT expenses, and firm profitability. Recent studies including Li et al. (2018) use this measure to capture organization capital. Following Eisfeldt and Papanikolaou (2013) with some modification, we measure organization capital with a firm's capitalized SG&A expenses less research and development (R&D) expenses from Compustat. SG&A expenses include training, consulting and information technology expenses, marketing, managerial compensation, and so forth, which are the elements to create organization capital (Lev (2000)). Typically, companies report SG&A expenses and R&D expenses separately. However, Compustat usually adds them together under the item XSGA, which is Selling, General, and Administrative Expense (Peters and Taylor (2017)). Thus, we subtract R&D expenses (XRD) from SG&A expense (XSGA) to get non-R&D SG&A expenses reported by the companies. Please see the details in Appendix B. The modified SG&A expenses are meant to reflect the firms' expenditures on key talent, and as such are aimed at improving a firm's productivity. Therefore, the modified SG&A expenses represent a firm's investment in organization capital.

Following Eisfeldt and Papanikolaou (2013) and Li et al. (2018), we use the perpetual inventory method to compute the stock of organization capital. Specifically, we recursively compute the stock of organization capital by cumulating the deflated value of SG&A expenses,

$$\text{OC}_{i,t} = (1 - \text{depr}_{\text{oc}})\text{OC}_{i,t-1} + \frac{\text{SG\&A}_{i,t}}{\text{cpi}_t}, \tag{1}$$

where depr_{oc} is the depreciation rate and cpi_t is the consumer price index. To implement the law of motion in equation (1), we choose an initial stock as follows:

$$\text{OC}_{i,0} = \frac{\text{SG\&A}_{i,1}}{g + \text{depr}_{\text{oc}}},$$

where the firm-specific growth rate of SG&A expenditure, g, is calculated as the average growth rate for each firm starting from the first observation in Compustat as early as 1950, which is the earliest year the Compustat has firm information. The depreciation rate of firm-level organization capital equals 15%,[12] which was the depreciation rate used by the Bureau of Economic Analysis (BEA) in its estimation of R&D capital in 2006 (Eisfeldt and Papanikolaou (2013)). $\text{SG\&A}_{i,1}$ is firm i's first nonmissing value of modified SG&A expenses in Compustat. We replace missing values of firm i's SG&A expenses with zero as well as missing values of firm i's R&D expenses with zero. After using equation (1) to get the raw organization capital, we scale it by the firm's book value of total assets and label it OC.

SG&A expenses include expenditures beyond investment in organization capital, for example, managerial perk consumption, restructuring, and audit fees. Thus, our measure of organization capital could be subject to noise. However, it is worth noting that this noisy measure biases against us finding a significant relationship between organization capital and the cost of bank loans. Nonetheless, we

[12]Our results are robust to using depreciation rates of 10%, 20%, 25%, 30%, 35%, and 40%.

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use multiple alternative measures of organization capital in our empirical analyses to mitigate the measurement concerns.

C. Bank Loan Spread and Total Cost of Borrowing

Our dependent variable is a firm's loan spread, AISD (all-in-spread-drawn). AISD is the interest rate spread over LIBOR plus facility fees for a loan facility. In addition, Berg et al. (2016) call for studies on bank loans to use the total cost of borrowing instead of simply the interest rate spread to capture the complexity of loan structures. We, therefore, conduct additional tests to investigate the effect of organization capital on the total cost of borrowing and its different components.

D. Summary Statistics

Table 1 reports summary statistics for our sample. We report detailed definitions of all variables in Appendix C. All continuous variables are winsorized at the 1st and 99th percentiles. The mean value of AISD is 194 basis points and the median value is 175 basis points. This value is consistent with the bank loan literature (e.g., Hasan, Hoi, Wu, and Zhang (2017)). The mean (median) value of the ratio of organization capital to total assets is 0.63 (0.43), which is comparable to the value in Li et al. (2018).

TABLE 1

Summary Statistics

Table 1 presents descriptive statistics on our sample of 29,221 loan-year observations for the period from 1982 to 2019. AISD is interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. TCB is total cost of borrowing from Berg et al. (2016) paper for the period from 1982 to 2011. AISU is sum of facility fees and commitment fees. COMMITMENT_FEES are fees paid on the unused amount of loan commitments. FACILITY_FEES are fees paid on the entire committed amount, regardless of usage. OC is constructed by cumulating firms *i*'s CPI-deflated selling, general and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year *t*, following Eisfeldt and Papanikolaou (2013). ASSETS are book value of total assets of firm *i* in year *t*. ROA is calculated as earnings before interests and taxes, scaled by lagged total assets. MB is calculated as ratio of book value assets less book value of equity plus market value of equity to book value of total assets of firm *i* at year *t*. LEVERAGE is the ratio of sum of short- and long-term debt to book value of total assets of firm *i* in year *t*. TANGIBILITY is the ratio of net property, plant, and equipment (PPE) to book value of total assets of firm *i* in year *t*. Z_SCORE is calculated $1.2 \times$ WCAP/AT $+ 1.4 \times$ RE/AT $+ 3.3 \times$ PI/AT $+0.6 \times$ E/L $+$ SALE/AT, where WCAP is working capital, AT is total assets, RE is retained earnings, and PI is pretax income, SALE is total sales, E is market value of equity, and L is total liabilities and. EARNINGS_VOLATILITY is the standard deviation of quarterly earnings from previous 12 quarters. FIRM_AGE is the number of years that the company has existed in Compustat database. ln(LOAN_SIZE) is the natural logarithm of dollar amount of the loan. ln(LOAN_MATURITY) is the natural logarithm of loan duration in months. SYNDICATION is a dummy variable equal to 1 if the loan is syndicated, and 0 otherwise.

	N	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
AISD	29,221	194.00	124.44	100.00	175.00	250.00
TCB	17,567	138.85	119.11	51.53	104.13	185.66
AISU	29,221	18.28	20.10	0.00	12.50	35.00
COMMITMENT_FEES	29,221	15.84	20.30	0.00	0.00	30.00
FACILITY_FEES	29,221	3.11	8.09	0.00	0.00	0.00
OC	29,221	0.63	0.62	0.20	0.43	0.84
ASSETS ($mil)	29,221	4,978.47	18,116.06	270.87	919.85	3,155.10
ROA	29,221	0.16	0.11	0.10	0.15	0.21
MB	29,221	2.82	4.20	1.26	2.10	3.45
LEVERAGE	29,221	0.31	0.22	0.16	0.28	0.42
TANGIBILITY	29,221	0.36	0.31	0.14	0.28	0.49
Z_SCORE	29,221	3.55	2.77	1.89	2.95	4.44
EARNINGS_VOLATILITY	29,221	0.51	0.72	0.13	0.26	0.55
FIRM_AGE	29,221	22.80	16.96	9.00	18.00	35.00
LOAN_SIZE ($mil)	29,221	356.78	559.21	50.00	150.00	400.00
LOAN_MATURITY (months)	29,221	50.46	21.51	36.00	60.00	60.00
SYNDICATION	29,221	0.93	0.26	1.00	1.00	1.00

IV. Empirical Results

A. Baseline Results

To test our hypotheses, following prior studies (e.g., Graham, Li, and Qiu (2008), Hasan et al. (2014), and Houston, Jiang, Lin, and Ma (2014)), we use the following specification:

$$
\begin{aligned}
(2)\quad \log(\text{AISD})_{i,t} = {} & \alpha + \beta_1 \text{OC}_{i,t-1} + \beta_2 \text{FIRM\_SIZE}_{i,t-1} + \beta_3 \text{ROA}_{i,t-1} + \beta_4 \text{MB}_{i,t-1} \\
& + \beta_5 \text{LEVERAGE}_{i,t-1} + \beta_6 \text{PPE}_{i,t-1} + \beta_7 \text{Z\_SCORE}_{i,t-1} \\
& + \beta_8 \text{EARNINGS\_VOLATILITY}_{i,t-1} + \beta_9 \text{FIRM\_AGE}_{i,t} \\
& + \beta_{10} \text{LOAN\_SIZE}_{i,t} + \beta_{11} \text{LOAN\_MATURITY}_{i,t} \\
& + \beta_{12} \text{SYNDICATION\_DUMMY}_{i,t} + \beta_{13} \text{CREDIT\_RATING}_{i,t-1} \\
& + \beta_{14} \text{TERM\_LOAN}_{i,t} + \text{LOAN\_PURPOSE\_FES} + \text{YEAR\_FES} \\
& + \text{INDUSTRY\_FES} + \epsilon_{i,t}.
\end{aligned}
$$

Table 2 reports the baseline regression results. In column 1, we examine the association between organization capital and a firm's loan spread, controlling for firm characteristics, loan characteristics, loan purpose fixed effects, year fixed effects, and industry fixed effects. The coefficient on organization capital is −0.039 and is significant at the 1% level, suggesting that banks value the performance-enhancing aspect of organization capital over its risk-engendering aspect. This finding is consistent with our Hypothesis 1a. In addition, our finding is economically meaningful. Specifically, a 1-standard-deviation increase in organization capital is associated with a loan spread decrease of 2.4%, on average. Given that the mean value of the spread is 194 basis points, this 2.4% decrease translates into a 4.7 basis points reduction.[13] The loan size and the time to maturity in our sample, on average, are $356.8 million and around 4.2 years, respectively. Taken together, this implies that a 1-standard-deviation increase in organization capital reduces total interest expenses per loan facility by $0.704 million ($0.704 = 356.8 \times 0.00047 \times 4.2$). Our estimate is also consistent with those reported in prior studies that provide evidence on factors that impact loan spread. For example, Bharath et al. (2008), Hasan et al. (2014), (2017), Li, Wang, and Wruck (2020), and Chakraborty, Leone, Minutti-Meza, and Phillips (2022) find that a 1-standard-deviation change in accounting quality, tax avoidance, social capital, accounting-based compensation horizon, and financial statement complexity in their respective samples is associated with a 6.65, 4.87, 4.33, 7.90, and 5.62 basis points change in loan spreads, respectively.

In column 2, we add lenders' fixed effects to the baseline model to mitigate lender-specific effects. The coefficient on organization capital is slightly larger and

[13]We also estimate the baseline regression without control variables. The coefficient on organization capital is −0.081, and it is significant at the 1% level. This translates into a 5% decrease in loan spread with a 1-standard-deviation increase in organization capital. We also examine how each control variable affects our results. We find that there is no single variable that has a dominating effect. The largest absorbing effect is by firm age. Without controlling for firm age, the economic magnitude is a 3.9% decrease in loan spreads with a 1-standard-deviation increase in organization capital.

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TABLE 2

Organization Capital and Bank Loan Spread: Baseline Results

Table 2 reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and the bank loan spread. The sample period is from 1982 to 2019. The dependent variable ln(AISD), calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. The testing variable is OC constructed by cumulating firms *i*'s CPI-deflated selling, general, and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year *t*, following Eisfeldt and Papanikolaou (2013). Column 1 shows the results of baseline regression with control variables and year, industry, and loan purpose fixed effects. Column 2 reports the results of regression with control variables and year, industry, loan purpose, and lender fixed effects. Column 3 repeats baseline analysis by replacing OC with residual of regression of OC on innovative capacity. Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: $\ln(\text{AISD})_{i,t}$		
	1	2	3
$\text{OC}_{i,t-1}$	−0.039***	−0.041***	
	(−3.20)	(−3.37)	
$\text{OC\_RESIDUAL\_ON\_IC}_{i,t-1}$			−0.037***
			(−3.05)
$\ln(\text{ASSETS})_{i,t-1}$	−0.135***	−0.133***	−0.133***
	(−16.45)	(−17.48)	(−17.42)
$\text{ROA}_{i,t-1}$	−0.747***	−0.671***	−0.669***
	(−13.42)	(−12.36)	(−12.29)
$\text{MB}_{i,t-1}$	−0.003**	−0.003***	−0.003***
	(−2.56)	(−2.65)	(−2.67)
$\text{LEVERAGE}_{i,t-1}$	0.392***	0.336***	0.336***
	(11.82)	(10.51)	(10.52)
$\text{TANGIBILITY}_{i,t-1}$	0.063***	0.064***	0.066***
	(2.60)	(2.79)	(2.88)
$\text{Z\_SCORE}_{i,t-1}$	−0.020***	−0.021***	−0.021***
	(−7.05)	(−7.58)	(−7.58)
$\text{EARNINGS\_VOLATILITY}_{i,t-1}$	0.084***	0.076***	0.076***
	(11.51)	(10.94)	(10.91)
$\text{FIRM\_AGE}_{i,t-1}$	−0.004***	−0.003***	−0.003***
	(−8.40)	(−7.97)	(−8.05)
$\ln(\text{LOAN\_SIZE})_{i,t}$	−0.117***	−0.106***	−0.107***
	(−13.88)	(−14.09)	(−14.11)
$\ln(\text{LOAN\_MATURITY})_{i,t}$	0.080***	0.073***	0.073***
	(8.41)	(8.04)	(8.03)
$\text{SYNDICATION}_{i,t}$	0.058***	0.045**	0.044**
	(2.98)	(2.38)	(2.37)
$\text{CREDIT\_RATINGS}_{i,t-1}$	0.082***	0.078***	0.078***
	(16.75)	(16.38)	(16.39)
$\text{TERM\_LOAN}_{i,t}$	0.326***	0.287***	0.287***
	(34.39)	(33.15)	(33.17)
Loan purpose FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Lender FE	No	Yes	No
No. of obs.	29,221	29,221	29,221
Adj. R^2	0.575	0.618	0.617

remains significant at the 1% level. This indicates that our result is not affected by lender-specific effects. The effects of the control variables on loan spreads are similar to those documented in the prior literature (e.g., Graham et al. (2008), Hasan et al. (2014), and Houston et al. (2014)). For instance, firm size, profitability, market-to-book ratio, Altman *Z*-score, firm age, and loan size are negatively related to loan spreads, while leverage, tangibility, earnings volatility, and loan maturity are positively related to loan spreads.

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One could argue that our measure of organization capital simply captures a firm's innovation. To mitigate this concern, we run a regression of organization capital on innovation capacity, and use the residual from the regression as the independent variable instead of the original measure of organization capital. Following Kumar and Li (2016), we define a firm's innovation capacity (IC) as its total asset growth in a year if the firm has nonmissing and nonzero R&D expenditure for the year, and 0 otherwise. Total asset growth is calculated as total assets at year t minus total assets at year $t-1$ scaled by total assets at year $t-1$. We report the result using this alternative measure of organization capital in column 3 in Table 2. Consistent with the original regression results, we find that this residual of the organization capital variable is negatively associated with loan spreads, and it is significant at the 1% level. In sum, we find that organization capital is negatively associated with loan spreads, suggesting that banks favorably factor in organization capital when pricing loans.

B. Alternative Measures of Organization Capital

As mentioned in Eisfeldt and Papanikolaou (2013) and Li et al. (2018), there are some concerns about the SG&A-based measure of organization capital. Although we believe that the primary input to SG&A expenses is investment in organization capital, such as employee training costs, IT investment, and consulting fees, there might also be some expenses unrelated to investment in organization capital, such as managerial perk consumption, restructuring, and audit fees. These unrelated expenses could obfuscate our measure of organization capital, thus raising concerns about our findings. To address this issue, we follow Li et al. (2018) and sort organization capital into deciles for each year and use the decile rankings instead of the continuous measure of organization capital. Column 1 in Table 3 presents the results when we rerun our baseline model using the decile ranking of the organization capital measure. Consistent with our baseline results, we find that a higher rank of organization capital is associated with a lower loan spread. This association is significant at the 1% level.

It could also be the case that each industry has different accounting practices that govern the expense components included in SG&A expenses which could lead to measurement error in our organization capital measure (Li et al. (2018)). Following Li et al. (2018), we address concerns about this type of measurement error by using the industry-median-adjusted ratio of organization capital to total assets as our independent variable. Column 2 in Table 3 reports the results. We find that industry-median-adjusted organization capital is negatively associated with loan spreads, and this association is significant at the 1% level.

To address the possibility that the measurement error comes from the two sources mentioned above, following Li et al. (2018), we combine the two approaches. Specifically, for each year, we rank firms into deciles based on the industry-median-adjusted ratio of organization capital to total assets. We use this ranking measure to proxy for organization capital. Column 3 in Table 3 presents the results. Consistent with our previous results, we find that the rank of industry-median-adjusted organization capital is negatively associated with the loan spread and is significant at the 1% level.

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TABLE 3

Organization Capital and Bank Loan Spread: Alternative Measures

Table 3 reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and bank loan spread, using alternative measures of organization capital, instead of direct construct measure used in the baseline model. The dependent variable ln(AISD), calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm i in year t. OC_Rank is the decile rank of organization capital of firm i in year $t-1$ based on Compustat universe. IND_ADJ_OC is organization capital of firm i minus the 2-digit SIC industry-median organization capital, scaled by the book value of total assets in year $t-1$. IND_ADJ_OC RANK is the decile rank of industry-median adjusted organization capital of firm i in year $t-1$ based on Compustat universe. SGA_DEPR is the ratio of capitalized SG&A expenses to total assets. Capitalized SG&A is calculated using a 5-year straight-line depreciation approach. SGA/AT is the ratio of SG&A expense to total assets. OC_LR is organization capital calculated following Lev et al. (2009). OC_PT is organization capital calculated by Peters and Taylor (2017). The control variables and the fixed effects are the same as those used in the baseline model in column 1 of Table 2 but are omitted for brevity. Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: $\ln(\text{AISD})_{i,t}$						
	1	2	3	4	5	6	7
$\text{OC\_RANK}_{i,t-1}$	−0.021***						
	(−7.52)						
$\text{IND\_ADJ\_OC}_{i,t-1}$		−0.039***					
		(−3.20)					
$\text{IND\_ADJ\_OC\_RANK}_{i,t-1}$			−0.013***				
			(−5.74)				
$\text{SGA\_DEPR}_{i,t-1}$				−0.089**			
				(−1.99)			
$\text{SGA/AT}_{i,t-1}$					−0.095**		
					(−2.31)		
$\text{OC\_LR}_{i,t-4,t-3,t-2,t-1,t}$						−0.167*	
						(−1.70)	
$\text{OC\_PT}_{i,t-1}$							−0.072**
							(−2.23)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	29,221	29,221	29,221	25,002	28,666	27,555	28,149
Adj. R^2	0.577	0.575	0.576	0.587	0.575	0.580	0.577

Next, following Li et al. (2018), we use a 5-year straight-line depreciation approach to capitalize SG&A expenses. The results are reported in column 4 in Table 3. This alternative organization capital measure is negatively associated with the loan spread and the association is significant at the 5% level. In column 5, we use the ratio of SG&A expenses to total assets as an alternative measure of organization capital, following Li et al. (2018). Again, this alternative measure of organization capital is negatively related to loan spreads and the relation is significant at the 5% level.

Eisfeldt and Papanikolaou (2013) argue that organization capital is both firm-specific and embedded in key talent. The measurement of organization capital used in our main tests is derived from a firm's SG&A expenditure. This measure is more likely to capture the part of organization capital that is embedded in key talent, since SG&A expenditure includes employee training expenses and managerial compensation. To test whether firm-specific organization capital affects the loan spread, we follow Lev et al. (2009) and measure a firm's organization capital as its abnormal profits compared to its industry peers in the same year.[14] By definition, organization

[14]See Lev et al. (2009) for measurement details.

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capital improves a firm's productivity. Thus, Lev et al. (2009) attribute abnormal profits relative to the industry average for firms with the same level of fixed assets, number of employees, and SG&A expenses to firm-specific organization capital. Column 6 in Table 3 shows that organization capital calculated using Lev et al.'s (2009) method is also negatively associated with the loan spread. This indicates that both organization capital embedded in key talent and firm-specific organization capital negatively affect the loan spread.

Our final alternative measure of organization capital is proposed by Peters and Taylor (2017). Similar to Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017) use the perpetual method to calculate organization capital, with the major difference being that they exclude R&D expenses from SG&A expenses and that the initial stock of organization capital starts from firms' founding years. Column 7 in Table 3 contains the results. Consistent with the results from the other organization capital measures, it shows that organization capital is negatively associated with the loan spread.

In sum, we use seven alternative measures of organization capital to address concerns raised by Eisfeldt and Papanikolaou (2013), Li et al. (2018), and others, that the baseline measure of organization capital we use is likely to be measured with error and, as such, that our finding could be adversely affected. In all of the alternative measures, we find that organization capital is negatively associated with loan spread. The fact that our results hold in all of our measures of organization capital gives us confidence that they are robust and less likely to be attributed to measurement error in our proxy for organization capital.

C. Identification Strategies

It is important to establish the causal effect of organization capital on the cost of bank loans. For example, there could be omitted variables that are correlated with both organization capital and the cost of bank loans, leading to a spurious relation between these two that is not causal. In addition, firms with lower spreads may have more funds available to invest in organization capital, rather than that high organization capital reduces the loan spread, leading to a reversed causal relation between these two. We address these concerns in this section.

1. Instrumental Variable Approach

To address the concern of omitted variables that could be correlated with both organization capital and the cost of bank loans, we employ the instrumental variable (IV) approach. An appropriate IV will extract the exogenous component of organization capital and relate it to the loan spread. That is, we need an IV that explains the variation in firms' investment in organization capital (the relevance condition) but is not associated with the firm-specific bank loan spread except through the channel of organization capital (the exclusion restriction).

Following Li et al. (2018), we use state-level unemployment insurance (UI) benefits as our IV. Organization capital is shared between the firm and the key talent, making the loss of talent the key risk for firms that invest in organization capital (Eisfeldt and Papanikolaou (2013), (2014)). Unemployment insurance benefits reduce firms' risk of losing talent by reducing employees' income

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risk. When facing a high risk of future unemployment and therefore, a high risk of income loss without unemployment insurance benefits, employees are reluctant to invest in firm-specific human capital. However, with unemployment insurance benefits, they are more willing to invest in human capital (Levhari and Weiss (1974), Brown and Kaufold (1988)). Furthermore, unemployment insurance benefits deter job resignations by removing employees' incentive to change jobs to "preempt" impending layoffs (Light and Omori (2004)). Therefore, unemployment insurance benefits reduce the likelihood of employees changing jobs and therefore reduce the firm's risk of losing talent. Furthermore, there is no theoretical or empirical evidence of a direct association between state-level unemployment insurance benefits and the firm-level bank loan spread. Therefore, unemployment insurance benefits can serve as a theoretically valid IV.

Following Hassler et al. (2005), we measure state-level unemployment benefits as the natural logarithm of the product of the maximum benefit amount and the maximum duration allowed. Unemployment insurance benefits data are obtained from the U.S. Department of Labor's database on Significant Provisions of State UI Laws (https://oui.doleta.gov/unemploy/statelaws.asp). The mean (median) dollar value of state-level unemployment benefits is \$9,581 (\$8,736).

Table 4 presents the 2SLS regression results. Column 1 shows the results of the first-stage model. The dependent variable in the first-stage model is organization capital. The coefficient on UI is positive and significant, suggesting that unemployment insurance benefits are positively associated with firms' investment in organization capital, and consistent with the work of Levhari and Weiss (1974), Brown and Kaufold (1988), and others. The mean (median) of predicted organization capital from the first stage is 0.63 (0.64) with a standard deviation of 0.25. Furthermore, the p-value of Cragg–Donald Wald's F statistic is 0.00, rejecting the null hypothesis that the instrument is weak (Cragg and Donald (1993), Stock and Yogo (2005)).

Column 2 presents the second-stage results where we regress loan spreads on the fitted value of organization capital. We find that the fitted organization capital variable is negatively associated with loan spreads and is statistically significant at the 5% level. Economically, a 1-standard-deviation increase in the fitted organization capital is associated with a 1.4% decrease in loan spreads. Given that the mean value of the spread is 194 basis points, this 1.4% decrease translates into a 2.7 basis points reduction in loan spreads.

2. Quasi-Natural Experiment

To address the reverse causality concern, we employ a quasi-natural experiment. We explore the staggered recognition of IDD by U.S. state courts. This legal doctrine is designed to prevent firms' former employees from working at rival companies if doing so would inevitably disclose the firms' trade secrets. One of the risks for firms of investing in organization capital is that it is shared between firms and the key talent (Eisfeldt and Papanikolaou (2013), (2014)). This means that firms bear the risk that their key talent will leave for rival firms. IDD reduces the risk of firms' investment in organization capital in two ways. First, it limits the job opportunities for employees who choose to leave their current employer because,

TABLE 4

Organization Capital and Bank Loan Spread: 2SLS Model

Table 4 reports the 2SLS regression results examining the relation between organization capital and the bank loan spread. The sample period is from 1982 to 2019. The dependent variable for each specification is at the top of each column. The first-stage regression result is reported in column 1. Column 1 uses state-level unemployment insurance (UI) benefit as the instrument for organization capital. UI benefit is calculated as the natural logarithm of the product of the maximum benefit amount and the maximum duration of states that firm *i* headquartered in year *t*, following Hassler et al. (2005). Column 2 examines the relation between organization capital and the loan spread, estimated using predicted organization capital from first stage regression reported in column 1. The dependent variable ln(AISD), is calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. Please refer to Appendix C for the detailed definitions of the control and instrumental variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable	
	$OC_{i,t-1}$	$\ln(AISD)_{i,t}$
	1st Stage	2nd Stage
	1	2
$UI_{i,t-1}$	0.065** (2.47)	
$PREDICTED\_OC_{i,t-1}$		−0.563** (−1.98)
$\ln(ASSETS)_{i,t-1}$	−0.132*** (−19.42)	−0.204*** (−5.21)
$ROA_{i,t-1}$	0.108 (1.59)	−0.693*** (−10.92)
$MB_{i,t-1}$	0.005*** (3.60)	−0.000 (−0.20)
$LEVERAGE_{i,t-1}$	−0.054 (−1.19)	0.364*** (9.90)
$TANGIBILITY_{i,t-1}$	−0.338*** (−12.92)	−0.114 (−1.15)
$Z\_SCORE_{i,t-1}$	−0.001 (−0.32)	−0.021*** (−7.18)
$EARNINGS\_VOLATILITY_{i,t-1}$	0.050*** (5.66)	0.110*** (6.79)
$FIRM\_AGE_{i,t-1}$	0.008*** (13.36)	0.000 (0.17)
$\ln(LOAN\_SIZE)_{i,t}$	0.017*** (3.53)	−0.108*** (−11.09)
$\ln(LOAN\_MATURITY)_{i,t}$	−0.010 (−1.15)	0.074*** (7.55)
$SYNDICATION_{i,t}$	0.010 (0.46)	0.064*** (3.24)
$CREDIT\_RATINGS_{i,t-1}$	−0.006 (−0.99)	0.079*** (15.22)
$TERM\_LOAN_{i,t}$	−0.016** (−2.18)	0.318*** (29.72)
P-value of Cragg–Donald Wald's *F* statistic	0.000	
Loan purpose FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
No. of obs.	29,221	29,221
Adj. R^2	0.419	0.574

they are not allowed to work for rival firms if doing so would cause leakage of their former employers' trade secrets. Thus, IDD, to some degree, prevents employees from leaving their current jobs. Second, even if key talents do change jobs, the fact that they cannot work for rival firms helps secure their former employers' trade secrets. Therefore, job changes of key talent should not hurt firms in states that

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adopt IDD as much as firms in states that do not adopt IDD. Thus, we expect that firms headquartered in states adopting IDD will be more likely to invest in organization capital than firms headquartered in other states. In addition, firms will be more likely to invest in organization capital after their state has adopted IDD than before. Thus, the IDD adoption setting provides an appropriate quasi-natural experiment to address endogeneity concerns related to causality issues.

Following Klasa, Ortiz-Molina, Serfling, and Srinivasan (2018), we create an IDD index based on state-by-state case law on trade secrets. In constructing the index, we identify the timing of the precedent-setting cases made by state courts that changed the state courts' positions concerning IDD. Twenty-one states adopted IDD. We assign a value of 1 to those states, starting on the date of the precedent-setting case in each state. In addition, 3 states dropped their previous adoption of IDD with precedent-setting cases. For those 3 states, we assign a value of zero starting on the date of the precedent-setting case for rejection. We assign a value of 0 to all other observations. We label this variable IDD. In addition, we create a dummy variable, TREAT, equal to 1 if a firm is in a state that adopted IDD at some point in time, and 0 if a firm is in a state that has never adopted IDD during our sample period. In untabulated results, we find that the average organization capital of firms in IDD-adopting states (TREAT = 1) is 0.65 and the average organization capital of firms in states without IDD (TREAT = 0) is 0.57, with the difference being significant at the 1% level. We also find that the average organization capital of firms in the IDD-adopting states is 0.59 before IDD adoption (TREAT = 1 and IDD = 0) and 0.66 after IDD adoption (TREAT = 1 and IDD = 1), with the difference again being significant at the 1% level.

Table 5 presents the multivariate results. The dependent variable is a firm's loan spread. In column 1, the coefficient on TREAT is insignificant and the coefficient on IDD is negative and significant at the 5% level. TREAT captures the effect for firms located in IDD-adopting states before the adoption compared to control firms that are in non-IDD-adopting states. The insignificant coefficient on TREAT indicates that there is no statistical difference in loan spreads for firms located in non-IDD-adopting states and those located in IDD-adopting states before the IDD adoption. The significant and negative coefficient on IDD indicates that firms located in IDD-adopting states enjoy a lower loan spread after the IDD adoption in the states, consistent with an increase in firms' organization capital investment induced by the adoption of IDD.

To further check if the result is caused by the possibility that IDD-adopting states have a different pattern of bank loan spreads, we perform a time trend test using a series of timing-related variables, PRE_2YR, PRE_1YR, POST_1YR, POST_2YR, POST > 2YR. PRE_2YR is a dummy variable equal to 1 for treatment firms 2 years before the states in which they are located recognize the IDD, and 0 otherwise; PRE_1YR is similarly defined. Post_1YR is a dummy variable equal to 1 for treatment firms 1 year after the states in which they are located recognize the IDD, and 0 otherwise; POST_2YR is similarly defined. POST > 2YR is a dummy variable equal to 1 for treatment firms more than 2 years after the states in which they are located recognize the IDD, and 0 otherwise.

If IDD-adopting states have a different pattern of bank loan spreads from non-IDD-adopting states, we should observe a significant difference between

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TABLE 5

Organization Capital and Bank Loan Spread: Quasi-Natural Experiment

Table 5 reports the results of the quasi-natural experiment that uses the staggered recognition of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts. This legal doctrine intends to prevent firms' former employees from working at rival firms if doing so would inevitably disclose the firms' trade secrets. The dependent variable ln(AISD), calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. TREAT is a dummy variable equal to 1 if a firm is in a state that recognizes the IDD at some time during our sample period and 0 otherwise. IDD is a dummy variable equal to 1 for treatment firms after their located states recognize the IDD and 0 otherwise. PRE_2YR is a dummy variable equal to 1 for treatment firms when it is 2 years before their located states recognize the IDD and 0 otherwise. Pre_1YR is a dummy variable equal to 1 for treatment firms when it is 1 year before their located states recognize the IDD and 0 otherwise. POST_1YR is a dummy variable equal to 1 for treatment firms when it is 1 year after their located states recognize the IDD and 0 otherwise. POST_2YR is a dummy variable equal to 1 for treatment firms when it is 2 years after their located states recognize the IDD and 0 otherwise. POST > 2YR is a dummy variable equal to 1 for treatment firms when it is more than 2 years after their located states recognize the IDD and 0 otherwise. Please refer to Appendix C for the detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: $\ln(\text{AISD})_{i,t}$	
	1	2
TREAT	0.025 (1.47)	0.022 (1.30)
$\text{IDD}_{i,t-1}$	−0.035** (−2.13)	
PRE_2YR		0.048 (1.03)
PRE_1YR		0.001 (0.03)
POST_1YR		0.042 (1.06)
POST_2YR		−0.055 (−1.41)
POST>2YR		−0.035** (−2.04)
$\ln(\text{ASSETS})_{i,t-1}$	−0.129*** (−15.91)	−0.129*** (−15.90)
$\text{ROA}_{i,t-1}$	−0.752*** (−13.33)	−0.755*** (−13.38)
$\text{MB}_{i,t-1}$	−0.003*** (−2.65)	−0.003*** (−2.62)
$\text{LEVERAGE}_{i,t-1}$	0.397*** (11.86)	0.398*** (11.87)
$\text{TANGIBILITY}_{i,t-1}$	0.075*** (3.12)	0.074*** (3.08)
$\text{Z\_SCORE}_{i,t-1}$	−0.020*** (−7.04)	−0.020*** (−7.02)
$\text{EARNINGS\_VOLATILITY}_{i,t-1}$	0.080*** (11.01)	0.081*** (11.00)
$\text{FIRM\_AGE}_{i,t-1}$	−0.004*** (−9.00)	−0.004*** (−8.97)
$\ln(\text{LOAN\_SIZE})_{i,t}$	−0.118*** (−13.90)	−0.118*** (−13.93)
$\ln(\text{LOAN\_MATURITY})_{i,t}$	0.079*** (8.32)	0.079*** (8.32)
$\text{SYNDICATION}_{i,t}$	0.057*** (2.85)	0.057*** (2.85)
$\text{CREDIT\_RATINGS}_{i,t-1}$	0.083*** (16.76)	0.083*** (16.74)
$\text{TERM\_LOAN}_{i,t}$	0.326*** (34.31)	0.326*** (34.29)
Loan purpose FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
No. of obs.	28,819	28,819
Adj. R^2	0.574	0.575

IDD-adopting states and non-IDD-adopting states before the adoption of the IDD. Observing such a difference would imply a violation of the parallel trend assumption that the trends in bank loan spreads of treatment firms in IDD-adopting states and control firms in non-IDD-adopting states are parallel prior to the IDD adoption, which would cast doubt on the validity of our difference-in-differences approach.

Column 2 in Table 5 presents the results. The coefficients on PRE_2YR and PRE_1YR are positive and not significant. This indicates that there is no significant difference in loan spreads between IDD-adopting states and non-IDD-adopting states before the IDD adoption, providing evidence that our setting satisfies the parallel trend assumption of difference-in-differences research design. The positive coefficients indicate that, if anything, IDD-adopting states have higher loan spreads than non-IDD-adopting states. To the extent that this is the case, it will bias against us finding lower loan spreads for IDD-adopting states after the IDD adoption. The coefficient on POST_1YR is positive but insignificant. The coefficient on POST_2YR is negative with a *t*-value of -1.41. The coefficient on POST > 2YR is negative and significant at the 5% level. Overall, these results show that loan spreads decrease only after the adoption of the IDD. Furthermore, it suggests that changes in organization capital are a slow-moving process (Dessein and Prat (2022)). Thus, our quasi-natural experiment results provide further evidence to support our main finding and mitigate endogeneity concerns.

3. Propensity Score Matching Approach

The propensity score matching approach helps to mitigate the problem of "functional form misspecification" if a relationship is misspecified (Shipman, Swanquist, and Whited (2017)). It matches a treatment group with a control group so that, ideally, both treatment and control groups have the same characteristics except for the treatment. If the treatment and control groups show different results based on the treatment after matching, it can be concluded that it is the treatment that leads to the different results. In our study, the treatment is a high investment in organization capital. To operationalize the propensity score matching approach, we match firms with more organization capital with firms with less organization capital so that they have similar firm characteristics except for their organization capital level. If we continue to find a significant difference in loan spreads when using the matched sample, we will be able to conclude that more organization capital results in lower bank loan spreads.

Specifically, we follow Francis et al. (2021) and sort firms into deciles based on their organization capital level for each year. We define those firms in the top (bottom) 3 deciles that have the highest (lowest) organization capital as high (low) OC firms and only retain those firms. Thus, our treatment group is comprised of high OC firms and our control group low OC firms. Columns 1–3 in Panel A of Table 6 report the difference between these two groups of firms in terms of their firm and loan characteristics. We can see that high OC firms are smaller in size, have lower ROA, have higher market-to-book ratios, are less leveraged, have fewer tangible assets, are less likely to go bankrupt, and are older. Their bank loans tend to be of shorter maturity, smaller, and are less likely to be syndicated. They are also characterized by lower credit ratings and are less likely to have term loans.

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TABLE 6

Organization Capital and Bank Loan Spread: Propensity Score Matching Approach

Table 6 reports the differences in the bank loan spread based on a sample where firms with more organization capital are matched to firms with less organization capital using a propensity score matching approach. The initial sample includes all sample firms that belong to the top and bottom 3 deciles based on their organization capital among the Compustat universe of firms. HIGH_OC (LOW_OC) firms are firms with the most (least) organization capital that belong to the top (bottom) 3 deciles. Panel A reports the differences in observables between HIGH_OC and LOW_OC firms. The PRE_MATCH column contains all HIGH_OC and LOW_OC firms. The POST_MATCH column contains the subsample of matched HIGH_OC–LOW_OC pairs after propensity score matching. Column 1 in Panel B presents the parameter estimates from the probit model used in estimating the propensity scores for HIGH_OC and LOW_OC firms. The dependent variable for column 1 in Panel B, HIGH_OC_DUMMY, is a dummy variable that equals 1 if the firm is a HIGH_OC firm and 0 otherwise. Column 2 in Panel B reports the multivariate result for the matched sample. It examines the relationship between organization capital and the loan spread, estimated using pooled OLS regression. The dependent variable ln(AISD), calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics or *Z*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Difference in Observables

	PRE_MATCH			POST_MATCH		
	HIGH_OC (n = 8,359)	LOW_OC (n = 8,154)	High–Low	HIGH_OC (n = 1,134)	LOW_OC (n = 1,134)	High–Low
Variable	1	2	3	4	5	6
ln(ASSETS)	6.38	7.28	−0.90***	6.70	6.68	0.02
ROA	0.16	0.17	−0.01*	0.16	0.17	−0.01***
MB	3.08	2.68	0.40***	2.82	3.09	−0.27
LEVERAGE	0.29	0.33	−0.04***	0.28	0.28	0.00
TANGIBILITY	0.30	0.42	−0.12***	0.31	0.31	0.00
Z_SCORE	3.84	3.28	0.56***	3.78	3.97	−0.19
EARNINGS_VOLATILITY	0.52	0.51	0.01	0.48	0.47	0.01
FIRM_AGE	24.76	20.32	4.44***	21.52	20.88	0.64
ln(LOAN_SIZE)	18.42	18.95	−0.53***	18.61	18.59	0.02
ln(LOAN_MATURITY)	3.76	3.79	−0.03***	3.78	3.74	0.04
SYNDICATION	0.92	0.94	−0.02***	0.93	0.93	0.00
CREDIT_RATINGS	0.88	1.32	−0.44***	1.04	0.99	0.05
TERM_LOAN	0.28	0.31	−0.03***	0.28	0.29	−0.01

Panel B. Multivariate Regressions

	Dependent Variable	
	$HIGH\_OC\_DUMMY_{i,t-1}$	$\ln(AISD)_{i,t}$
	1	2
$HIGH\_OC\_DUMMY_{i,t-1}$		−0.089***
		(−3.36)
$\ln(ASSETS)_{i,t-1}$	−0.442***	−0.150***
	(−16.24)	(−7.87)
$ROA_{i,t-1}$	0.685***	−0.794***
	(3.07)	(−6.26)
$MB_{i,t-1}$	0.018***	−0.012***
	(3.49)	(−3.86)
$LEVERAGE_{i,t-1}$	−0.114	0.373***
	(−0.75)	(4.92)
$TANGIBILITY_{i,t-1}$	−1.661***	0.144*
	(−13.46)	(1.96)
$Z\_SCORE_{i,t-1}$	0.008	−0.017***
	(0.76)	(−2.76)
$EARNINGS\_VOLATILITY_{i,t-1}$	0.125***	0.065***
	(4.16)	(3.95)
$FIRM\_AGE_{i,t-1}$	0.029***	−0.005***
	(12.85)	(−4.05)
$\ln(LOAN\_SIZE)_{i,t}$	0.056***	−0.120***
	(3.16)	(−7.19)
$\ln(LOAN\_MATURITY)_{i,t}$	−0.016	0.084***
	(−0.53)	(3.37)
$SYNDICATION_{i,t}$	0.249***	0.042
	(3.49)	(0.84)
$CREDIT\_RATINGS_{i,t-1}$	−0.049**	0.090***
	(−2.19)	(7.47)
$TERM\_LOAN_{i,t}$	−0.043	0.312***
	(−1.50)	(11.51)
Loan purpose FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
No. of obs.	16,513	2,268
Pseudo R^2	0.192	
Adj. R^2		0.614

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Because high OC firms are significantly different from low OC firms in terms of firm and loan characteristics, we match high OC firms with low OC firms in the same year and industry based on the firm and loan characteristics used in our baseline regression. We estimate the following probit model to conduct the propensity score matching:

$$\text{(3)} \qquad \text{TREATMENT}_{i,t} = \alpha + \gamma Z_{i,t} + \text{YEAR}_t + \text{INDUSTRY}_i + \epsilon_{i,t},$$

where TREATMENT equals 1 if a firm is in the high OC group and 0 otherwise. **Z** is a vector of control variables of firm and loan characteristics used in our baseline regression. Column 1 in Panel B of Table 6 presents the result of the probit regression.

Using the predicted propensity score from model (3), we conduct one-on-one nearest-neighbor propensity score matching by matching treatment firms with control firms with the closest propensity scores in the same year and industry. We also impose the restriction that the difference in propensity scores between the treatment and matched firms cannot exceed 0.01. This procedure produces 1,134 unique pairs of matched firms.

We investigate the accuracy of our propensity score matching approach by assessing the difference between the treatment group and the matched group using a *t*-test. We report the results in Panel A of Table 6. Column 6 shows that the treatment and control groups have similar characteristics except for ROA. It should be noted that although, ideally, we should not find any differences between the two groups, it is not unusual for differences in some characteristics to be present. The fact that there is only one significant variable, indicates that our matching is appropriate.

Using the matched groups, we provide multivariate regression results that examine the difference in loan spreads between the treatment and matched groups. The result shown in column 2 in Panel B of Table 6 indicates that high OC firms face lower loan spreads than low OC firms, with the coefficient being significant at the 1% level. Thus, the propensity score matching result is consistent with our baseline result.

In summary, after using different approaches to address endogeneity concerns and establish causality, we are confident to conclude that the relation between organization capital and the cost of bank loans is likely to be causal.

D. Organization Capital, the Total Cost of Borrowing, and Its Components

The total borrowing costs of bank loans include both the interest rate spread and fees. Berg et al. (2016) argue that banks use fees to price options embedded in the loan contracts and to screen borrowers. Different loan pricing structures may cumulatively yield comparable total costs of borrowing. For example, Berg et al. (2017) find that, although loans in the U.S. and Europe have different pricing structures, there is not a significant difference in the total cost of borrowing between them. We, therefore, examine how organization capital affects the total cost of borrowing and its components including different types of fees.

We first investigate the effect of organization capital on the total cost of borrowing and AISU. The total cost of borrowing consists of both AISD and AISU. The data are drawn from Berg et al. (2016) and cover the period from 1986 to 2011.

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We provide detailed definitions of the variables in Appendix C. AISU comprises facility fees and commitment fees. We use OLS regression with the natural logarithm of the total cost of borrowing as the dependent variable to mitigate the concern that the result is driven by extreme values. We use a Tobit regression model when analyzing AISU individually, because the value of AISU is censored above zero and more than one-quarter of the loans in our sample have no AISU. Table 7 reports the results. We find that organization capital is negatively and significantly related to both the total cost of borrowing and AISU. Thus, organization capital has a similar negative effect on both the cost of borrowing and AISU.

TABLE 7

Organization Capital and Total Cost of Borrowing/All-In-Spread-Undrawn

Table 7 reports the regression results examining the relation between organization capital and total cost of borrowing as well as the relation between organization capital and AISU. Column 1 uses pooled OLS model and column 2 uses Tobit model. The dependent variable in column 1, ln(TCB), is calculated as the natural logarithm of the total cost of borrowing from Berg et al. (2016). The dependent variable in column 2 is AISU. The testing variable is OC constructed by cumulating firms *i*'s CPI-deflated selling, general, and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year *t*, following Eisfeldt and Papanikolaou (2013). Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable	
	ln(TCB)	AISU
	1 OLS	2 Tobit
$OC_{i,t-1}$	−0.041***	−0.557***
	(−3.19)	(−2.93)
$ln(ASSETS)_{i,t-1}$	−0.190***	−1.744***
	(−24.73)	(−17.43)
$ROA_{i,t-1}$	−0.864***	−14.694***
	(−12.78)	(−14.12)
$MB_{i,t-1}$	−0.003*	−0.029
	(−1.83)	(−1.27)
$LEVERAGE_{i,t-1}$	0.552***	5.441***
	(14.30)	(9.62)
$TANGIBILITY_{i,t-1}$	0.056**	1.839***
	(1.98)	(4.27)
$Z\_SCORE_{i,t-1}$	−0.027***	−0.266***
	(−7.78)	(−5.43)
$EARNINGS\_VOLATILITY_{i,t-1}$	0.100***	1.395***
	(10.39)	(10.34)
$FIRM\_AGE_{i,t-1}$	−0.004***	−0.054***
	(−7.19)	(−7.87)
$ln(LOAN\_SIZE)_{i,t}$	−0.043***	−0.727***
	(−6.47)	(−7.41)
$ln(LOAN\_MATURITY)_{i,t}$	−0.159***	2.544***
	(−16.21)	(14.33)
$SYNDICATION_{i,t}$	0.089***	5.550***
	(4.54)	(13.65)
$CREDIT\_RATINGS_{i,t-1}$	0.079***	1.516***
	(14.41)	(17.75)
$TERM\_LOAN_{i,t}$	1.006***	−27.170***
	(87.86)	(−126.36)
Loan purpose FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
No. of obs.	17,567	29,221
Adj. R^2	0.733	
Pseudo R^2		0.0625

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Next, we investigate the impact of organization capital on the two components of AISU, facility fees, and commitment fees. Fees are the prices of options embedded in the loan contracts, for example, value transfer from lenders to borrowers with a credit line, and are higher for high-volatility firms (Berg et al. (2016)). Organization capital, as a risky investment, could increase the uncertainty of future cash flows. Banks may use fees to account for this risk. Because both facility fees and commitment fees are censored above zero, we use the Tobit model for both regressions.

Table 8 reports the results. Column 1 shows that organization capital is positively associated with facility fees. This is consistent with Berg et al.'s (2016) argument that high-volatility firms are associated with higher fees. We also provide supportive evidence in column 2 that organization capital is positively associated with future 5-year ROA volatility.[15] This provides empirical evidence that firms with high organization capital are more volatile. Column 3 reports that organization capital is negatively associated with commitment fees. Commitment fees are the fees paid on the unused amount of a loan. Berg et al. (2016) argue that borrowers can signal a lower use of credit lines by selecting a lower commitment fee. Consistent with this argument, we find that firms with high organization capital have lower usage of credit lines 3 years after loan origination. This result is reported in column 4.

E. Underlying Mechanism of Key Talent

Eisfeldt and Papanikolaou (2013) point out that organization capital is embedded in the key talent within the firm. In this subsection, we investigate whether key talent is a possible underlying mechanism. One of the important types of key talent for a firm is inventors. Chemmanur, Kong, Krishnan, and Yu (2019) argue that firms with high top management human capital could attract more inventors. Further, firms with high organization capital could likely employ more inventors because organization capital is shared between the firm and its key talent (Eisfeldt and Papanikolaou (2013)). Finally, more inventors could produce more innovation output, increasing firms' profitability potential. We directly test the association between organization capital and inventors.

We first test the association between organization capital and inventor mobility, denoted by NET_INFLOW_OF_INVENTORS, using inventor data obtained from Li et al. (2014) (https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15705). The data cover the period up to 2010. Following Marx, Strumsky, and Fleming (2009) and Chemmanur et al. (2019), we define inventor mobility as employee inventors changing firms, and identify this based on their reporting of two successive patent applications for two different firms.[16] Thus, we retain those inventors who have filed at least two patent applications throughout

[15]We also use the future 3-year ROA volatility and the future 5-year (and 3-year) volatilities of operating cash flows scaled by total assets, instead of the future 5-year ROA volatility, and find consistent results.

[16]We use the patent database created by Kogan, Papanikolaou, Seru, and Stoffman (2017). The database is located at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

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TABLE 8
Organization Capital and Fees

Table 8 reports the regression results examining the relation between organization capital and facility fees as well as commitment fees. The sample period is from 1982 to 2019. The dependent variable in column 1 is FACILITY_FEES and the dependent variable in column 3 is COMMITMENT_FEES. The dependent variable in column 2 is RETURN_ON_ASSETS (ROA) volatility in the next 5 years. The dependent variable in column 4 is the 3-year usage rates for revolvers after loan origination. The testing variable is OC constructed by cumulating firms *i*'s CPI-deflated selling, general, and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year *t*, following Eisfeldt and Papanikolaou (2013). Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	FACILITY_FEES	FIVE_YEAR_ROA_VOLATILITY	COMMITMENT_FEES	USAGE_RATES
	1 Tobit	2 OLS	3 Tobit	4 OLS
$OC_{i,t-1}$	0.242**	0.005**	−0.750***	−0.019*
	(2.54)	(2.21)	(−3.61)	(−1.95)
$\ln(ASSETS)_{i,t-1}$	0.415***	−0.008***	−2.193***	−0.057***
	(8.26)	(−15.72)	(−20.03)	(−14.41)
$ROA_{i,t-1}$	−0.592	0.032***	−15.887***	−0.202***
	(−1.13)	(3.65)	(−13.95)	(−3.34)
$MB_{i,t-1}$	0.022*	0.001***	−0.034	0.001
	(1.91)	(2.78)	(−1.37)	(0.56)
$LEVERAGE_{i,t-1}$	−0.797***	0.002	6.648***	0.227***
	(−2.80)	(0.41)	(10.74)	(7.70)
$TANGIBILITY_{i,t-1}$	−0.257	0.006	2.613***	0.064***
	(−1.19)	(1.50)	(5.54)	(2.74)
$Z\_SCORE_{i,t-1}$	−0.071***	0.002***	−0.158***	−0.005*
	(−2.89)	(5.83)	(−2.95)	(−1.75)
$EARNINGS\_VOLATILITY_{i,t-1}$	−0.279***	0.003***	1.658***	0.008
	(−4.12)	(3.22)	(11.23)	(1.33)
$FIRM\_AGE_{i,t-1}$	0.025***	−0.000***	−0.077***	−0.000
	(7.31)	(−3.59)	(−10.28)	(−0.35)
$\ln(LOAN\_SIZE)_{i,t}$	0.478***		−1.102***	0.015***
	(9.69)		(−10.26)	(3.77)
$\ln(LOAN\_MATURITY)_{i,t}$	−0.384***		2.614***	−0.018**
	(−4.31)		(13.46)	(−2.13)
$SYNDICATION_{i,t}$	0.584***		5.245***	0.038
	(2.86)		(11.79)	(1.09)
$CREDIT\_RATINGS_{i,t-1}$	−0.125***	0.001***	1.424***	−0.022***
	(−2.92)	(2.73)	(15.23)	(−5.44)
$TERM\_LOAN_{i,t}$	−2.477***		−22.395***	
	(−22.92)		(−95.19)	
Loan purpose FE	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	29,221	17,784	29,221	5,863
Pseudo R^2	0.0160		0.0463	
Adj. R^2		0.193		0.366

the database. We assume that an inventor starts her employment at a firm in the year that she files her first patent application for the firm in which she is employed, and ends her employment at the first firm and starts her employment at subsequent firms in the years she files her first patent applications for the subsequent firms. Following Chemmanur et al. (2019), we also assume that inventors stay with the last firm we identify in the database. Once we have identified move-in and move-out years and companies for each inventor, we aggregate the total number of move-in (inflow) inventors and the total number of move-out (outflow) inventors for each firm in

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each year. The NET_INFLOW_OF_INVENTORS for each firm in each year is calculated as the natural logarithm of 1 plus the inflow for that firm in that year minus the natural logarithm of 1 plus the outflow for that firm in that year. We assign zero to firm-year observations without any net flow of inventors. Column 1 in Table 9 reports the result. The coefficient on organization capital is positive and significant at the 1% level, providing strong support for the argument that firms with higher organization capital attract more inventors.

Francis et al. (2021) find that organization capital influences borrowers' innovation output. Chemmanur et al. (2019) also document a positive association between top management human capital and corporate innovation. Because we provide evidence that organization capital is embedded in inventors, the next step is to test the association between organization capital and innovation. We use 3 proxies for innovation: ADJ_PATENTS, ADJ_CITES, and ADJ_CITES_PER_PATENT.

TABLE 9

Organization Capital and Key-Talent Mechanism

Table 9 reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and key talents/innovation output within the firm. The dependent variable in column 1 is NET_INFLOW_OF_INVENTORS, calculated as the natural logarithm of 1 plus the inflow of inventors to firm *i* in year *t* minus the natural logarithm of 1 plus the outflow of inventors from firm *i* in year *t*, following Chemmanur et al. (2019). The dependent variable in column 2 is ADJ_PATENTS, calculated as the natural logarithm of 1 plus the class-adjusted patent count for firm *i* in year *t*, following Chemmanur et al. (2019). The dependent variable in column 3 is ADJ_CITES, calculated as the natural logarithm of 1 plus the class-adjusted total number of citations received by firm *i*'s patents filed in year *t*, following Chemmanur et al. (2019). The dependent variable in column 4 is ADJ_CITES_PER_PATENT, calculated as the natural logarithm of 1 plus the total number of class-adjusted citations received by firm *i*'s patents in year *t*, normalized by 1 plus the total number of class-adjusted patents applied by firm *i* in year *t*, following Chemmanur et al. (2019). All continuous variables are winsorized at the 1st and 99th percentiles. Please refer to Appendix C for detailed definitions of the control variables. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	NET_INFLOW_OF_INVENTORS$_{i,t}$	ADJ_PATENTS$_{i,t}$	ADJ_CITES$_{i,t}$	ADJ_CITES_PER_PATENT$_{i,t}$
	1	2	3	4
OC$_{i,t-1}$	0.037***	0.080***	0.011***	0.001***
	(3.25)	(5.16)	(4.11)	(3.85)
ln(ASSETS)$_{i,t-1}$	0.114***	0.180***	0.028***	0.002***
	(17.73)	(19.90)	(15.26)	(14.73)
ROA$_{i,t-1}$	0.041	−0.058	−0.001	0.000
	(0.81)	(−1.04)	(−0.14)	(0.12)
MB$_{i,t-1}$	0.006***	0.005***	0.001***	0.000*
	(4.27)	(2.97)	(2.99)	(1.72)
LEVERAGE$_{i,t-1}$	−0.111***	−0.130***	−0.015**	−0.001**
	(−3.29)	(−3.18)	(−2.10)	(−1.97)
TANGIBILITY$_{i,t-1}$	−0.035	−0.022	−0.005	−0.001
	(−1.31)	(−0.70)	(−0.78)	(−1.30)
Z_SCORE$_{i,t-1}$	0.008***	0.007***	0.000	0.000
	(3.48)	(2.75)	(0.99)	(1.04)
EARNINGS_VOLATILITY$_{i,t-1}$	−0.014*	−0.001	−0.000	0.000
	(−1.73)	(−0.13)	(−0.24)	(0.87)
FIRM_AGE$_{i,t-1}$	0.002**	0.004***	0.001***	0.000***
	(2.42)	(6.13)	(6.65)	(4.70)
CREDIT_RATINGS$_{i,t-1}$	−0.019***	−0.033***	−0.007***	−0.000**
	(−3.75)	(−5.16)	(−5.61)	(−2.16)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	13,293	17,829	17,829	17,829
Adj. R^2	0.297	0.413	0.300	0.237

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ADJ_PATENTS is the natural logarithm of 1 plus the class-adjusted patent count for a firm each year, following Chemmanur et al. (2019). Because the lag between patent applications and patent granting is usually several years, using the raw number of patents would result in a bias against firm-year observations in the most recent years. Following Seru (2014) and Chemmanur et al. (2019), we account for this bias by scaling each patent for each firm-year observation by the mean number of patents in that year for all firms in the same 3-digit technology class as the patent. Column 2 in Table 9 presents the result, which shows that the coefficient on organization capital is positive and significant at the 1% level.

Following Chemmanur et al. (2019), we define ADJ_CITES as the natural logarithm of 1 plus the class-adjusted total number of citations received by the patents filed by a firm in a certain year. Like patents, citations are subject to truncation bias because they are usually received over a long period of time. Consequently, the raw citation counts would be biased against the patents filed in the most recent years. Again, following Seru (2014) and Chemmanur et al. (2019), we correct this bias by dividing the citations of a given patent by the total number of citations received by all patents in the same 3-digit technology class in that year. Column 3 reports the result, showing that the coefficient on organization capital is positive and significant at the 1% level.

Following Chemmanur et al. (2019), ADJ_CITES_PER_PATENT is the natural logarithm of 1 plus the total number of class-adjusted citations received by a firm's patents in a given year, normalized by 1 plus the total number of class-adjusted patents applied for by that firm in that year. Column 4 reports the result. We find that the coefficient on organization capital is positive and significant at the 1% level. Overall, we find a positive association between a firm's organization capital and its innovation output.

F. Organization Capital and Bank Loan Spread by Industries

Our baseline results and robustness results show that the value-enhancing feature of organization capital dominates its risk-engendering feature. In this section, we investigate whether the effect of organization capital on bank loan spreads varies across industries. We separate our sample into 10 industries using Fama–French 12-industry classification.[17] Table 10 shows the results. We find that organization capital has a negative and significant effect on loan spreads in four industries: consumer nondurables, manufacturing, energy, and chemicals. The coefficients on organization capital are negative but insignificant in two industries: wholesale, retail, and services as well as healthcare. The coefficients on organization capital are positive but insignificant in four industries: consumer durables, business equipment, telecommunication, and others. Organization capital is defined as partly firm-specific and partly embedded in a firm's key talent. Based on the definition of organization capital, there is no theoretical reason to conjecture that it is also industry-specific. Our results provide support for that. The finding that organization capital is significant for only 4 out of 10 industries

[17]Given that utilities and financial institutions are regulated industries, we exclude both from our sample.

TABLE 10

Organization Capital and Bank Loan Spread by Industry

Table 10 reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and the bank loan spread for different industries. The sample period is from 1982 to 2019. The dependent variable ln(AISD), calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. The testing variable is OC constructed by cumulating firms *i*'s CPI-deflated selling, general, and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year *t*, following Eisfeldt and Papanikolaou (2013). Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable									
Industry	Consumer Nondurables	Consumer Durables	Manufacturing	Energy	Chemicals	Business Equipment	Telecommunication	Wholesale, Retail, and services	Healthcare	Other
	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$
	1	2	3	4	5	6	7	8	9	10
$\text{OC}_{i,t-1}$	−0.069*	0.035	−0.149***	−0.236***	−0.137***	0.033	0.069	−0.014	−0.007	0.009
	(−1.67)	(0.59)	(−3.90)	(−3.69)	(−3.03)	(1.10)	(1.21)	(−0.62)	(−0.15)	(0.38)
$\ln(\text{ASSETS})_{i,t-1}$	−0.178***	−0.166***	−0.120***	−0.178***	−0.097***	−0.062***	−0.138***	−0.177***	−0.150***	−0.154***
	(−6.14)	(−5.11)	(−5.91)	(−11.21)	(−3.02)	(−3.48)	(−6.43)	(−7.29)	(−5.59)	(−9.42)
$\text{ROA}_{i,t-1}$	−1.017***	−1.216***	−0.727***	−0.206*	−0.627	−0.603***	−0.823***	−1.077***	−0.436**	−0.638***
	(−4.35)	(−3.63)	(−4.62)	(−1.74)	(−1.65)	(−4.93)	(−4.60)	(−6.05)	(−2.36)	(−4.62)
$\text{MB}_{i,t-1}$	−0.009	−0.009**	0.001	0.000	−0.008	−0.008***	0.001	0.000	−0.007*	−0.004*
	(−1.20)	(−2.07)	(0.40)	(0.02)	(−1.51)	(−2.66)	(0.54)	(0.09)	(−1.86)	(−1.67)
$\text{LEVERAGE}_{i,t-1}$	0.435***	0.569***	0.613***	0.176	0.469**	0.497***	0.147*	0.394***	0.460***	0.350***
	(2.61)	(3.81)	(7.69)	(1.63)	(2.30)	(6.07)	(1.78)	(5.06)	(4.03)	(4.52)
$\text{TANGIBILITY}_{i,t-1}$	0.023	0.128	−0.101	0.047	−0.072	0.061	0.292***	−0.124	−0.067	0.109**
	(0.17)	(0.82)	(−1.30)	(0.93)	(−0.70)	(0.65)	(5.59)	(−1.60)	(−0.82)	(2.33)
$\text{Z\_SCORE}_{i,t-1}$	−0.013	−0.019	−0.034***	−0.026***	−0.027	−0.011**	−0.010	−0.029***	−0.006	−0.027***
	(−1.02)	(−1.01)	(−4.40)	(−3.32)	(−1.12)	(−2.10)	(−0.82)	(−3.89)	(−0.76)	(−3.69)
$\text{EARNINGS\_VOLATILITY}_{i,t-1}$	0.093***	0.148***	0.076***	0.057***	0.087***	0.031**	0.071***	0.071***	0.087***	0.085***
	(4.48)	(5.27)	(4.02)	(3.08)	(2.74)	(2.09)	(3.95)	(3.80)	(2.79)	(4.06)
$\text{FIRM\_AGE}_{i,t-1}$	−0.004**	−0.002	−0.003***	−0.005***	−0.004**	−0.004***	−0.004***	−0.004***	−0.006***	−0.003**
	(−2.31)	(−1.27)	(−2.89)	(−3.89)	(−2.60)	(−3.50)	(−2.84)	(−3.92)	(−3.27)	(−2.30)
$\ln(\text{LOAN\_SIZE})_{i,t}$	−0.089***	−0.057**	−0.145***	−0.117***	−0.205***	−0.162***	−0.088***	−0.067***	−0.121***	−0.088***
	(−3.85)	(−1.98)	(−6.61)	(−6.88)	(−6.02)	(−7.92)	(−4.89)	(−3.36)	(−5.09)	(−5.63)

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TABLE 10 (continued)

Organization Capital and Bank Loan Spread by Industry

	Dependent Variable									
Industry	Consumer Nondurables	Consumer Durables	Manufacturing	Energy	Chemicals	Business Equipment	Telecommunication	Wholesale, Retail, and services	Healthcare	Other
	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$
	1	2	3	4	5	6	7	8	9	10
$\ln(\text{LOAN\_MATURITY})_{i,t}$	0.052**	0.028	0.072***	0.049	0.160***	0.116***	0.109**	0.071***	0.148***	0.052**
	(2.08)	(0.65)	(3.03)	(1.51)	(4.38)	(4.86)	(2.35)	(3.27)	(4.24)	(2.30)
$\text{SYNDICATION}_{i,t}$	0.187**	−0.080	0.017	0.070	0.070	0.067	−0.100	0.043	0.034	0.020
	(2.27)	(−0.94)	(0.34)	(0.86)	(0.69)	(1.62)	(−0.88)	(1.04)	(0.55)	(0.42)
$\text{CREDIT\_RATINGS}_{i,t-1}$	0.107***	0.107***	0.075***	0.042***	0.078***	0.067***	0.107***	0.093***	0.108***	0.080***
	(6.00)	(4.48)	(6.79)	(3.07)	(3.93)	(6.24)	(5.87)	(7.61)	(5.74)	(6.31)
$\text{TERM\_LOAN}_{i,t}$	0.313***	0.363***	0.311***	0.453***	0.366***	0.329***	0.196***	0.364***	0.219***	0.274***
	(11.24)	(10.00)	(14.84)	(10.85)	(9.56)	(14.45)	(7.73)	(12.89)	(8.06)	(13.31)
Loan purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,568	1,231	5,223	2,225	1,333	4,046	1,534	4,918	2,076	4,067
Adj. R^2	0.651	0.521	0.572	0.630	0.642	0.568	0.649	0.556	0.655	0.530

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corroborates the notion that organization capital is firm-specific and embedded in a firm's key talent. Moreover, the finding that only the negative effect is significant, suggests that in those four industries banks value the value-enhancing characteristic of organization capital more than they are concerned with its risk-increasing characteristic, consistent with the documented firm-level evidence. Overall, the industry-level results provide further evidence that organization capital negatively affects bank loan spread and key talent is an important driver.

V. Conclusion

In this article, we investigate the effect of a particular type of intangible assets, organization capital, on a firm's cost of capital by examining whether organization capital significantly impacts the cost of bank loans. Using a sample of U.S. firms over the period from 1982 to 2019, we provide robust evidence that firms with higher organization capital enjoy lower bank loan spreads. These results are robust to alternative measures of organization capital. In addition, we use propensity score matching, 2SLS with an IV, and a quasi-natural experiment to mitigate endogeneity concerns, and find consistent results. Furthermore, we find that organization capital is positively associated with facility fees and negatively associated with commitment fees. This is consistent with Berg et al.'s (2016) argument that facility fees reflect the prices of options embedded in bank loans and are higher for high-volatility firms, and that banks use commitment fees to screen borrowers. Borrowers select lower commitment fees if they anticipate a lower usage rate of bank loans. In addition, we investigate the possible mechanism(s) underlying the effect of organization capital on bank loans. We find a positive association between organization capital and the presence of inventors as well as between organization capital and innovation outputs.

In sum, our study contributes to the growing literature studying the role and value of organization capital and the broader literature on financial contracting. It highlights the influence of organization capital on firm value in the case of bank loans, as well as provides additional insights into the relationship between intangible assets and financial contracting. Our study complements our understanding of the economic benefits of organization capital to firms.

Appendix A. Organization Capital and Credit Ratings

In this appendix, we use four examples to illustrate how credit agencies (i.e., S&P Global) consider the four elements of organization capital in their credit analysis. All the examples are from S&P Global (2018).

Related to the element of human capital, in 2015, S&P placed Iconix Brand Group Inc. on CreditWatch negative when its CEO, COO, and CFO depart, partly because of the worry that incoming management does not "competently execute its current strategies." Related to the element of values and norms, in May 2017, S&P upgraded PG&E Corp., because it implemented a safety culture with tangible results, focusing on the needs of its customers after the 2010 San Bruno gas transmission explosion. Related to the element of knowledge and expertise, in the summer of 2017, Equifax experienced a significant data breach. Following that, S&P revised the outlook of the company to negative, reflecting the company's inability of data security. Related to the element of processes and practices, On Oct. 13, 2016, S&P upgraded Carnival Corp.'s credit rating because the firm had implemented sufficient risk mitigation and safety measures following multiple ship fires and other accidents. S&P believed that these measures would lessen the likelihood and severity of future potential damaging events on ships and therefore limit cash flow volatility.

Appendix B. Sample Selection and Additional Robustness Tests

In this appendix, we describe our sample selection process related to organization capital. We start with Compustat data set from 1950 to 2019. Organization capital is the cumulative SG&A expense. First, we obtain SG&A expenses from Compustat. Typically, companies report SG&A and R&D expenses separately. However, Compustat usually adds them together under the item XSGA, Selling, General and Administrative Expense (Peters and Taylor (2017)). To get non-R&D SG&A expenses reported by the companies, we subtract R&D expenses (XRD) from SG&A expenses (XSGA). In addition, when a firm externally acquires R&D on products that have not been sold yet, this R&D is expensed as In-Process R&D (RDIP) and it does not appear on the balance sheet. Compustat only adds R&D excluding In-Process R&D to XSGA (Peters and Taylor (2017)). We closely follow Peters and Taylor (2017) in this regard and calculate a firm's SG&A as Compustat variable XSGA minus XRD minus RDIP. We subtract instead of adding RDIP because Compustat codes this variable as negative. Although Compustat usually adds SG&A expense and R&D expense together, there are some exceptions. For example, if the company allocates R&D expense to cost of goods sold (COGS), XSGA does not include R&D expense. We follow Peters and Taylor (2017) and add the following screen in calculating SG&A: When XRD is greater than XSGA but is less than COGS, SG&A is equal to XSGA with no adjustments. In addition, we set XSGA equal to 0 if it is missing in Compustat.

We then use this modified SG&A to calculate the yearly growth rate of SG&A for each firm. We take the average growth rate for each firm as the proxy for the firm-specific investment rate of organization capital, which is g that is used to calculate the initial stock of organization capital. We remove firms that have a negative value of g. We assume the first observation of a firm in Compustat as its year 1. We calculate the initial stock of a firm's organization capital from the first year that it has a nonmissing and nonzero value of modified SG&A expense. A firm's first nonmissing Compustat record usually coincides with its initial public offering (IPO) (Peters and Taylor (2017)). We acknowledge that there is a time-lapse between a firm's founding year and its appearance in Compustat. However, we do not think this will affect our empirical results. Peters and Taylor (2017) calculate the initial stock from both a firm's founding year and its first appearance in Compustat and find consistent results. They state that using the first appearance in Compustat is a simpler alternative way. This is possibly because yearly SG&A's contribution to organization capital diminishes as years pass. The median age between founding year and IPO is 8 (Peters and Taylor (2017)) and the median age from a firm's first appearance in Compustat in our sample is 18. So the accumulated SG&A from pre-IPO years contributes a very small part of organization capital in our sample. In addition, we conduct a robustness test

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using Peters and Taylor's (2017) measure calculated from the founding years and find consistent results as shown in column 7 in Table 3.

We include all the firms regardless of how long they exist in Compustat. The minimum firm age in our sample is 2 with the mean (median) of 22.8 (18). Thus, the majority of firms in our sample exist for a long time. Therefore, we do not think that our results are driven by firms with only a few years' worth of observations in Compustat. Nevertheless, we conduct additional robustness tests. First, we remove new entrants in our baseline sample. The results are reported in Table A1. Column 1 defines new entrants as firms with starting firm age of 2 in our sample. Column 2 defines new entrants as firms with starting firm age of 2 or 3 in our sample. Column 3 defines new entrants as firms with starting firm age of 2 or 3 or 4 in our sample. Column 4 defines new entrants as firms with starting firm age of 2 or 3 or 4 or 5 in our sample. In all 4 columns, the coefficients on OC continue to be negative and significant. This indicates that our baseline results are robust to alternative samples removing new entrants.

Second, we remove short-lived firms in our baseline sample. The results are reported in Table A2. Column 1 defines short-lived firms as firms with ending firm age of 2 in our sample. Column 2 defines short-lived firms as firms with ending firm age of 2 or 3 in our sample. Column 3 defines short-lived firms as firms with ending firm age of 2 or 3 or 4 in our sample. Column 4 defines short-lived firms as firms with ending firm age of 2 or 3 or 4 or 5 in our sample. In all 4 columns, the coefficients on OC continue to be negative and significant. This indicates that our baseline results are robust to alternative samples removing short-lived firms.

TABLE A1

Organization Capital and Bank Loan Spread: Removing New Entrants

Table A1 reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and the bank loan spread after removing new entrants in our baseline sample. The sample period is from 1982 to 2019. The dependent variable ln(AISD), calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm *i* in year *t*. The testing variable is OC constructed by cumulating firms *i*'s CPI-deflated selling, general, and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year *t*, following Eisfeldt and Papanikolaou (2013). Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. *T*-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$
	1	2	3	4
Remove firms with starting firm age	=2	=2 or 3	=2 or 3 or 4	=2 or 3 or 4 or 5
$\text{OC}_{i,t-1}$	−0.040***	−0.041***	−0.033**	−0.027*
	(−3.08)	(−2.90)	(−2.26)	(−1.78)
$\ln(\text{ASSETS})_{i,t-1}$	−0.129***	−0.128***	−0.126***	−0.127***
	(−15.33)	(−14.34)	(−13.38)	(−12.83)
$\text{ROA}_{i,t-1}$	−0.756***	−0.799***	−0.799***	−0.834***
	(−12.39)	(−11.65)	(−10.36)	(−10.01)
$\text{MB}_{i,t-1}$	−0.004***	−0.003**	−0.005***	−0.005***
	(−2.67)	(−2.47)	(−3.55)	(−3.41)
$\text{LEVERAGE}_{i,t-1}$	0.399***	0.404***	0.415***	0.425***
	(11.28)	(10.85)	(10.35)	(9.93)
$\text{TANGIBILITY}_{i,t-1}$	0.049*	0.026	0.025	0.026
	(1.80)	(0.87)	(0.76)	(0.76)
$\text{Z\_SCORE}_{i,t-1}$	−0.019***	−0.019***	−0.020***	−0.021***
	(−6.30)	(−5.90)	(−5.32)	(−5.55)
$\text{EARNINGS\_VOLATILITY}_{i,t-1}$	0.086***	0.090***	0.085***	0.090***
	(11.06)	(10.24)	(8.89)	(8.70)

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TABLE A1 (continued)

Organization Capital and Bank Loan Spread: Removing New Entrants

	Dependent Variable			
	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$	$\ln(\text{AISD})_{i,t}$
	1	2	3	4
$\text{FIRM\_AGE}_{i,t-1}$	−0.004***	−0.004***	−0.004***	−0.003***
	(−7.81)	(−7.25)	(−6.59)	(−6.08)
$\ln(\text{LOAN\_SIZE})_{i,t}$	−0.125***	−0.130***	−0.134***	−0.138***
	(−15.26)	(−14.92)	(−14.27)	(−13.88)
$\ln(\text{LOAN\_MATURITY})_{i,t}$	0.088***	0.089***	0.094***	0.094***
	(8.98)	(8.74)	(8.75)	(8.48)
$\text{SYNDICATION}_{i,t}$	0.068***	0.077***	0.080***	0.088***
	(3.28)	(3.50)	(3.38)	(3.48)
$\text{CREDIT\_RATINGS}_{i,t-1}$	0.085***	0.091***	0.096***	0.101***
	(16.29)	(16.31)	(15.82)	(16.22)
$\text{TERM\_LOAN}_{i,t}$	0.327***	0.326***	0.328***	0.330***
	(33.64)	(31.14)	(28.74)	(27.87)
Loan purpose FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	26,341	23,294	20,581	18,703
Adj. R^2	0.581	0.589	0.595	0.602

TABLE A2

Organization Capital and Bank Loan Spread: Removing Short-Lived Firms

Table A2 reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and the bank loan spread after removing firms with only a few years' observations in our sample. The sample period is from 1982 to 2019. The dependent variable ln(AISD), is calculated as the natural logarithm of interest spread over LIBOR plus facility fees for a loan facility of firm i in year t. The testing variable is OC constructed by cumulating firms i's CPI-deflated selling, general, and administrative (SG&A) expenditures excluding research and development (R&D) expenses using a perpetual inventory method with firm-specific growth rate, scaled by total assets at year t, following Eisfeldt and Papanikolaou (2013). Please refer to Appendix C for detailed definitions of the control variables. All continuous variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: $\ln(\text{AISD})_{i,t}$			
	1	2	3	4
Remove firms with ending firm age	= 2	= 2 or 3	= 2 or 3 or 4	= 2 or 3 or 4 or 5
$\text{OC}_{i,t-1}$	−0.039***	−0.038***	−0.036***	−0.035***
	(−3.19)	(−3.08)	(−2.89)	(−2.74)
$\ln(\text{ASSETS})_{i,t-1}$	−0.134***	−0.134***	−0.133***	−0.133***
	(−16.38)	(−16.28)	(−16.06)	(−15.93)
$\text{ROA}_{i,t-1}$	−0.748***	−0.758***	−0.760***	−0.765***
	(−13.27)	(−13.21)	(−12.82)	(−12.49)
$\text{MB}_{i,t-1}$	−0.003**	−0.003**	−0.003**	−0.003**
	(−2.57)	(−2.55)	(−2.54)	(−2.47)
$\text{LEVERAGE}_{i,t-1}$	0.393***	0.397***	0.400***	0.403***
	(11.82)	(11.93)	(11.91)	(11.87)
$\text{TANGIBILITY}_{i,t-1}$	0.062**	0.057**	0.055**	0.049*
	(2.52)	(2.26)	(2.14)	(1.87)
$\text{Z\_SCORE}_{i,t-1}$	−0.020***	−0.021***	−0.021***	−0.021***
	(−7.02)	(−7.00)	(−6.96)	(−6.89)
$\text{EARNINGS\_VOLATILITY}_{i,t-1}$	0.084***	0.084***	0.084***	0.083***
	(11.50)	(11.40)	(11.38)	(11.28)
$\text{FIRM\_AGE}_{i,t-1}$	−0.004***	−0.004***	−0.004***	−0.004***
	(−8.37)	(−8.33)	(−8.26)	(−8.12)
$\ln(\text{LOAN\_SIZE})_{i,t}$	−0.117***	−0.117***	−0.118***	−0.118***
	(−13.89)	(−13.88)	(−13.89)	(−13.75)

(continued on next page)

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TABLE A2 (continued)

Organization Capital and Bank Loan Spread: Removing Short-Lived Firms

	Dependent Variable: ln(AISD)$_{i,t}$			
	1	2	3	4
ln(LOAN_MATURITY)$_{i,t}$	0.081***	0.083***	0.084***	0.085***
	(8.51)	(8.69)	(8.84)	(8.84)
SYNDICATION$_{i,t}$	0.061***	0.063***	0.068***	0.068***
	(3.08)	(3.16)	(3.34)	(3.29)
CREDIT_RATINGS$_{i,t-1}$	0.082***	0.082***	0.082***	0.082***
	(16.72)	(16.65)	(16.51)	(16.46)
TERM_LOAN$_{i,t}$	0.326***	0.326***	0.328***	0.329***
	(34.32)	(34.19)	(33.99)	(33.81)
Loan purpose FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	29,144	28,985	28,662	28,314
Adj. R^2	0.575	0.576	0.577	0.577

Appendix C. Variable Definitions

Dependent Variables

AISD: All-in-spread-drawn, defined as the sum of the interest rate spread over LIBOR plus the facility fees, from Dealscan.

TCB: The natural logarithm of total cost of borrowing from Berg et al. (2016).

The measure of total cost of borrowing is calculated as:

$$\begin{aligned}\text{TCB}=&\text{UPFRONT\_FEE/EXPECTED\_LOAN\_MATURITY\_IN\_YEARS}\\&+(1-1\text{PDD})\times(\text{FACILITY\_FEE}+\text{COMMITMENT\_FEE})\\&+\text{PDD}\times(\text{FACILITY\_FEE}+\text{SPREAD})\\&+\text{PDD}\times\text{Prob}\,(\text{UTILIZATION}>\text{UTILIZATION\_THRESHOLD}\\&\,|\text{USAGE}>0)\times\text{UTILIZATION\_FEE}\\&+\text{Prob}\,(\text{CANCELATION})\times\text{CANCELATION\_FEE},\end{aligned}$$

where TCB is total cost of borrowing and PDD is the likelihood of the credit line is drawn down. PDD equals 1 if the loan is a term loan.

AISU: All-in-spread-undrawn, defined as the sum of the facility fees and the commitment fees, from Dealscan.

FACILITY_FEES: Fees paid on the entire committed amount, regardless of usage, from Dealscan.

COMMITMENT_FEES: Fees paid on the unused amount of loan commitments, from Dealscan.

USAGE_RATES: 3-year-average loan usage rate after loan initiation. The usage rate is calculated as outstanding revolving credit / (outstanding revolving credit + undrawn revolving credit), from Capital IQ.

Organization Capital Related Variables

OC$_{i,t}$: Stock of organization capital, scaled by book value of total assets, in year t constructed by cumulating firms i's CPI-deflated selling, general and

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administrative (SG&A) expenditures using a perpetual inventory method (Eisfeldt and Papanikolaou (2013)).

OC_RANK$_{i,t}$: Decile rank of organization capital of firm i in year t based on Compustat universe.

IND_ADJ_OC$_{i,t}$: Organization capital of firm i minus the 2-digit SIC industry-median organization capital, scaled by book value of total assets in year t.

IND_ADJ_OC_RANK$_{i,t}$: Decile rank of industy-median adjusted organization capital of firm i in year t based on Compustat universe.

SGA_DEPR$_{i,t}$: The ratio of capitalized SG&A expenses to total assets. Capitalized SG&A is calculated using a 5-year straight-line depreciation approach.

SGA/AT$_{i,t}$: The ratio of SG&A expense to total assets.

OC_LR$_{i,t-4,t-3,t-2,t-1,t}$: Organization capital calculated following Lev et al. (2009).

OC_PT$_{i,t}$: Organization capital calculated by Peters and Taylor (2017).

IC$_{i,t}$: If firm i at year t has nonmissing and nonzero R&D expenditure, then IC equals the total assets growth, calculated as total assets at year t minus total assets at year $t-1$ scaled by total assets at year $t-1$, and 0 otherwise.

Firm Characteristics Variables

ln(ASSETS)$_{i,t}$: Natural logarithm of book value of total assets of firm i in year t.

ROA$_{i,t}$: Earnings before interests and taxes, scaled by lagged total assets.

MB$_{i,t}$: Ratio of (book value of assets − book value of equity + market value of equity) to book value of total assets of firm i in year t.

LEVERAGE$_{i,t}$: Ratio of sum of short- and long-term debt to book value of total assets of firm i in year t.

TANGIBILITY$_{i,t}$: Ratio of net property, plant, and equipment (PPE) to book value of total assets of firm i in year t.

Z_SCORE$_{i,t}$: Using $Z = 1.2(X_1) + 1.4(X_2) + 3.3(X_3) + 0.6(X_4) + 1(X_5)$ from modified Altman (1968) model in Graham, Li, and Qiu (2008), where X_1 is working capital scaled by total assets, X_2 is retained earnings scaled by total assets, X_3 is earnings before interest and taxes scaled by total assets, X_4 is market value of equity over book value of total liability, and X_5 is sales scaled by total assets.

EARNINGS_VOLATILITY$_{i,t}$: Standard deviation of quarterly earnings from previous 12 quarters.

FIRM_AGE: The number of years between the first year that a firm exists in Compustat and year t.

CREDIT_RATINGS: Equals 1 if Standard & Poor's long-term debt ratings are in the range from A− to AAA; equals 2 if Standard and Poor's long-term debt ratings are in the range from BBB− to BBB+; equals 3 if Standard and Poor's long term debt ratings is in the range from B− to BB+; equals 0 if the firm does not have Standard and Poor's long term debt ratings; and 4 otherwise.

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Loan Characteristics Variables

ln(LOAN_SIZE): The natural logarithm of dollar amount of the loan.

ln(LOAN_MATURITY): The natural logarithm of loan duration in months.

SYNDICATION: Dummy variable equal to 1 if the loan is syndicated, and 0 otherwise.

TERM_LOAN: Dummy variable equals 1 if the loan is a term loan. Term loans are defined as loans with type "Term Loan," "Term Loan A"-"Term Loan H," or "Delay Draw Term Loan" as indicated in the facility table in Dealscan.

Instrumental Variables

$UI_{i,t}$: The natural logarithm of the product of the maximum benefit amount and the maximum duration of states that firm *i* headquartered in year *t*, following Hassler et al. (2005).

Quasi-Natural Experiment Variables

TREAT: Equals 1 if a firm is headquartered in a state that adopts Inevitable Disclosure Doctrine (IDD) in a precedent-setting case and 0 if a firm is headquartered in the states that have never explicitly considered IDD in the court.

IDD: Equals 1 if a firm is headquartered in a state that adopts Inevitable Disclosure Doctrine (IDD) in a precedent-setting case starting the year of adoption, and equals 0 in all years preceding the date of the precedent-setting case. If the state subsequently rejects the IDD with another precedent-setting case, the index reverts to zero beginning the year it is rejected. For the states that have never explicitly considered IDD in the court, their IDD indexes are zero over the sample period.

Mechanism Variables

$\text{NET\_INFLOW\_OF\_INVENTORS}_{i,t}$: Natural logarithm of 1 plus inventor inflow for firm *i* in year *t* minus natural logarithm of 1 plus inventor outflow for firm *i* in year *t*.

$\text{ADJ\_PATENTS}_{i,t}$: Natural logarithm of 1 plus the class-adjusted patent counts for firm *i* in year *t*. Class-adjusted patent is calculated by scaling each patent for each firm-year observation by the mean number of patents for all firms for that year in the same 3-digit technology class as the patent.

$\text{ADJ\_CITATIONS}_{i,t}$: Natural logarithm of 1 plus the class-adjusted total number of citation counts received by firm *i*'s patents filed in year *t*. Class-adjusted citation counts are calculated by dividing citations of a given patent by the total number of citations received by all patents in the same 3-digit technology class as the patent in that year.

$\text{ADJ\_CITATIONS\_PER\_PATENT}_{i,t}$: Natural logarithm of dividing 1 plus the total number of class-adjusted citation counts received by firm *i* for all its patents in year *t* over 1 plus the total number of class-adjusted patents that firm *i* applied for in year *t*.

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