# Artificial Intelligence Capacity and the Cost of Debt

**Yutao Li**
Dhillon School of Business
University of Lethbridge
yutao.li@uleth.ca

**Hui (Eva) Liang**
School of Management and Economics
Chinese University of Hong Kong
lianghui@cuhk.edu.cn

**Wenye Tang**
Walker College of Business
Appalachian State University
tangw1@appstate.edu

**Ye Wang**
Ted Rogers School of Management
Toronto Metropolitan University
ye4.wang@torontomu.ca

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**ABSTRACT**

This study examines the impact of a borrower's Artificial Intelligence (AI) capacity on its cost of debt. Using data from Revelio Labs, we develop a firm-level AI capacity measure and find a negative association between AI capacity and loan spreads. Further analysis reveals that the reduction in cost of debt for high AI capacity is concentrated in borrowers facing high product market competition and borrowers with a greater amount of R&D, capital expenditures, and low leverage. Our study offers novel empirical evidence on how creditors price AI technology, contributing to both accounting and finance research and AI-related business studies.

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### 1. INTRODUCTION

Artificial Intelligence (AI) technology, a key component of Industry 4.0 (Ahmed, Jeon, and Piccialli 2022; Cen, Han, Qiu, and Wu 2024), has had a transformative impact on business practices as evidenced by a significant increase in AI-related patents and corporate AI investment (Stanford 2024). Unlike traditional data processing technologies, AI develops "human-like intelligence" by leveraging vast amounts of data through machine learning to perform complex tasks (Agrawal, Gans, and Goldfarb 2019; Davenport and Ronanki 2018). Academic research has documented that firm AI investments stimulate production innovation (Babina, Fedyk, He, and Hodson 2024), enhance process optimisation (Senoner, Netland, and Feuerriegel 2022), and improve trend prediction (Choi, Liu, and Shin 2024). However, few studies have explored the impact of AI investments on firms' external financing activities, especially in the private debt market. This study aims to fill this gap by investigating whether and how firms' AI-related investments influence their cost of debt.

In contrast to traditional technologies that rely on predetermined instructions, AI can "learn" and "think" independently, processing large amounts of data to generate cognitive knowledge, and facilitate interaction with humans (Brynjolfsson, Rock, and Syverson 2019; The Royal Institution 2023). On one hand, AI may reduce the cost of debt, given its potential to enhance a borrower's future cash flows by strengthening its competitive position in product market (e.g., Cockburn, Henderson, and Stern 2018; Huang, Xu, Xue, and Zhu 2023; Babina et al. 2024) and to improve a borrower's information environment (Anantharaman, Rozario, and Zhang 2023; Ding et al. 2020). On the other hand, AI fundamentally is a complicated new technology and its performance can still be unstable (Munoko, Brown-Liburd, and Vasarhelyi 2020; Osoba, Welser IV, and Welser 2017), and successful implementation of AI technologies requires not only technical expertise but also supporting resources and an appropriate organisational culture (Deloitte 2022). Given these complexities, it remains unclear whether and how lenders value a borrower's AI capacity.

To examine our research question, we utilize a unique human capital dataset Revelio Labs to construct a measure of firm-level AI capacity. Revelio collects and provides workforce information based on publicly available online job postings, professional profiles, employee sentiment reviews. We utilise the Individual Resume dataset spanning 2010 to 2018 to identify AI-skilled workers affiliated with each individual company. We merge Company-AI employee data with Compustat and compute the total number of AI-Skilled workers and ratio of AI-workers to total number of employees for each matched Compustat company in each year. We then use Dealscan_Compustat Linking Database provided by Michael Roberts to match the Compustat-AI capacity data with Dealscan's syndicated loan data. We obtain a sample of 11,195 loan facilities issued by 2,227 companies with all required variables available in year 2011-2019.

Our primary analysis reveals that a borrower with a higher AI capacity (i.e., a higher percentage of AI workers) has a lower cost of debt. The economic magnitude of the reduction in cost of debt is also significant. For every 1% increase in AI-worker ratio, the cost of debt is reduced by about 2.3%, equivalent to 5 basis points of the average of loan spread. We also show that the negative relationship between AI capacity and cost of debt is more pronounced in borrowers facing higher product market competition, [1] implying that creditors value AI's potential on stimulating product innovation.

We conduct several cross-sectional tests to further explore the effects of potential moderating factors on the relationship between borrower AI capacity and the cost of debt. To effectively leverage AI technology and maximise the benefits of AI investments, firms must be equipped with sufficient resources and adopt the right mindset (Commerford, Dennis, Joe, and Ulla 2022; Estep, Griffith, and MacKenzie 2024; Higgins 2005). To explore whether creditors' pricing of AI capacity depends on a borrower's investment capacity, we analyze the relationship between cost of debt and AI capacity for samples of borrowers with high and low research and development expenditure (R&D spending) and capital expenditure. We find that the negative relationship between AI capacity and cost of debt concentrates in borrowers with high R&D spending and capital expenditures.[2] We also explore whether the impact of AI compacity on cost of debt is through an alternative channel—the information channel and do not find evidence supporting information channel.

We conduct several additional tests to strengthen the inferences of our main findings. First, if AI capacity reduces a borrower's cost of debt by lowering default risk, we would expect a negative association between AI capacity and a borrower's future credit risk. Consistent with this expectation, we find that higher AI capacity is associated with lower expected default frequency and bond downgrading in three years. Second, we rerun our main tests using total number of AI employees and average ratio of AI employees over two years before the loan syndication year as

[1] We use Hoberg, Phillips, and Prabhala (2014) product market fluidity index to measure product market competition.
[2] Untabulated results also show that creditors price AI capacity only when a borrower has lower leverage, suggesting that creditors might be concerned over the financial burden created by AI investments and are only willing to lower cost of debt for a high AI capacity borrower if the borrower has high debt capacity (lower leverage). The results are available upon request.

alternative measures of AI capacity, and the results remain consistent, further supporting our conclusions. In the contrary, when we use the ratio of AI employees in one and two-year after loan syndication to predict cost of debt, we find that future AI employee ratios are not associated with current cost of debt, ruling out the concern that our results are due to spurious relationship between cost of debt and AI capacity.

Additionally, we investigate the relationship between firm AI capacity and several non-pricing terms commonly included in loan agreements, including the number of financial covenants, collateral requirements, loan maturity, and loan size. We do not find any significant association between a borrower's AI capacity and these non-pricing terms. The results that there is no significant relationship between AI capacity and debt covenants and collateral requirement are different from the findings in Kim, Song, and Stratopoulos (2018) that creditors impose fewer financial/non-financial covenants and are less likely to require collateral in loan contracts for borrowers with strong IT reputations. Together with our findings that a borrower's information environment does not moderate the relationship between cost of debt and AI capacity, [3] our results suggest that lenders value a borrower's AI technology differently from how they value more traditional IT capabilities and that creditors may perceive that AI technology have a more profound impact on a borrower.

Our study contributes to the accounting and banking literature in several ways. First, while prior research has explored the theoretical benefits of AI technology for bank lenders (e.g., Fuster, Goldsmith-Pinkham, Ramadorai, and Walther 2022; Jansen, Nguyen, and Shams 2020; Khandani, Kim, and Lo 2010), most of these studies focus on how creditors can employ AI technologies to

[3] Kim et al. (2018) document that a borrower's information environment moderates the effect of IT reputation on cost of debt, collateral requirements, and the number of covenants included in debt contracts.

improve their operation efficiencies. Given AI technologies evolve rapidly engendering huge public sentiment and AI hiring frenzy in recent years (Seth 2024), how financial markets value this new and uncertain technology becomes compelling. Our novel empirical evidence shows that creditors lower cost of debt for borrowers with high AI capacity and the reduction in cost of debt concentrates in borrowers facing more intensive product market competition and borrowers with greater capacity in R&D and capital expenditures. Our study offers new insights on how capital market values AI technologies. Secondly, our study identifies the potential channels through which AI technology influences creditors' valuation. While Anantharaman et al. (2023) demonstrate that AI technology can enhance firms' financial reporting systems, our findings suggest that creditors may not perceive the benefits of AI capacity for improved information quality as the first order effect and price such benefits accordingly. Our results that AI technologies affect cost of debt through its effect on enhancing a borrower's competitive position rather than though its effect on a borrower's information environment suggests that AI technologies' impacts on businesses and creditors' valuation might be different from those of traditional data-processing systems (i.e., IT reputation) (Kim et al. 2018).

The remainder of this paper is structured as follows: Section 2 discusses the literature background and develops our main hypothesis. Section 3 details the data construction and the sampling process. Section 4 presents our baseline and cross-sectional tests results. Section 5 reports the additional test results. Section 6 concludes the study.

## 2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### 2.1 Artificial Intelligence: definition and the impact

Artificial Intelligence (AI) is recognised as a pivotal technology of Industry 4.0 (Ahmed et.al. 2022) and has been widely adopted across various business activities (e.g., Cao, Jiang, Wang, and Yang 2024; Fedyk, Hodson, Khimich, and Fedyk 2022; Fuster et al. 2022). The textbook definition (e.g., Russell and Norvig 2016; Poole and Mackworth 2010) of Artificial Intelligence (AI) describes it as a machine-based system capable of mimicking human intelligence. It recognises patterns from vast amounts of data to perform highly sophisticated tasks, including prediction, detection, and classification (Agrawal et al. 2019; Luger and Stubblefield 2008; Russell and Norvig 2016). Unlike earlier technologies such as Enterprise Resource Planning system or data analytics, AI does not depend on explicitly coded human knowledge for analysis (Brynjolfsson et al. 2019). Instead, it “learns” directly from unstructured, high-dimensional data (e.g., text or images) and models non-linear relationships, significantly enhancing the speed and accuracy of analysis (Anantharaman et al. 2023; Saon et al. 2017). The rapid advancements in AI's technical capabilities have driven a significant surge in AI capacity. Stanford University's AI Index Report (Stanford 2024) reveals a dramatic rise in AI patents granted, increasing from fewer than 10,000 in 2010 to over 60,000 in 2022. This trend highlights firms' accelerated investments in AI to secure their future competitive advantages and create firm value (Brynjolfsson et al. 2019).

There are two fundamental channels for AI technology to increase firms’ productivity and firm value. First, it is argued that AI technology can create more business opportunities and enhance firms’ competitiveness by facilitating product innovation (Babina et al. 2024; Huang et al. 2023). Specifically, AI technology has the potential to transform corporate innovation by expanding firms' knowledge resources to generate novel ideas and enhancing the efficiency of their implementation (Bahoo, Cucculelli, and Qamar 2023; Cockburn et al. 2018). For instance, by leveraging AI-based natural language processing technology, firms can generate novel ideas for new product development by analysing online customer information (Hwang, Singh, and Argote 2019). Similarly, AI can enhance the design of new products and services by analysing customer-related data (Verganti, Vendraminelli, and Iansiti 2020) and improve knowledge integration, facilitating more effective innovative activities (Viberg and Eslami 2020). As a result, AI technology, can efficiently create unique value that is difficult for others to replicate, enabling firms to achieve a competitive advantage (Huang et al. 2023).

Another way AI can enhance firm performance is by improving production efficiency, primarily through cost reduction (Babina et al. 2024). The key driver of cost reduction is the "displacement effect," where human labor is substituted with machines. Since most industries require multitasking capabilities in their production processes, AI technology can exponentially enhance these capabilities through automation, reducing per unit labor costs (Acemoglu and Restrepo 2018; Ballestar, Díaz-Chao, Sainz, and Torrent-Sellens 2020). Empirical studies have documented displacement effect in specific industries (Agrawal et al. 2019; Fedyk et al. 2022). Additionally, AI's superior analytical and forecasting capabilities can help firms better leverage their data resources to enhance production planning and support more effective strategic decision-making (Fosso Wamba, Akter, Trinchera, and De Bourmont 2019; Tanaka, Bloom, David, and Koga 2020). For example, Khandani et al. (2010) show that employing machine learning techniques to predict consumer credit risk achieves savings of up to 25% of lenders' total losses, compared to traditional statistical methods. Similarly, using U.S. mortgage data, Fuster et al. (2022) show that machine learning technology delivers significantly higher predictive accuracy when forecasting mortgage default risk. Wang et al. (2020) demonstrate that AI algorithms enhance trend prediction and classification accuracy in the production processes of petrochemical companies, thereby improving their process efficiency.

### 2.2 Hypothesis Development: Artificial Intelligence and cost of debt

Classic economic theory suggests that a firm's cost of debt is determined by its default risk and the liquidation value of its assets (Merton 1974). In other words, from a lender's perspective, their primary concerns are the likelihood of any default on the loans and the proportion of the loan's face value that can be recovered in the event of default (Cheng and Subramanyam 2008; Valta 2012). The likelihood of a borrower's default hinges on the availability of sufficient cash flow to meet interest and principal payments (Plumlee, Xie, Yan, and Yu 2015), while the expected recovery amount for a lender is affected by the value of the borrower's assets that can serve as re-deployable collateral (Benmelech and Bergman 2009). Since a borrower's AI capacity may not directly qualify as traditional collateral (Brown, Martinsson, and Petersen 2013; Hall 2010), the relationship between firm AI capacity and cost of debt mainly depends on how these investments influence the firms' future cash flow.

As discussed in the last section, AI technology can generate business opportunities and competitive advantages for firms through product innovation, while also lowering operational costs by improving process efficiency. If that is the case, possessing strong AI capabilities signals significant potential for robust future cash flow, alleviating lenders' concerns about default risk and uncertainty. Therefore, it is reasonable to predict that a borrower's AI capacity should lead to a lower cost of debt.

However, this may not necessarily be the case. First, the theoretical benefits of AI technology may not be fully realised. Successful implementation of new business strategy requires alignment with organisational factors such as structure, resource availability, and culture (Higgins 2005). Not all firms possess the capacity to effectively manage their AI capacity (Deloitte 2022). For instance, recent studies suggest that AI technology may enhance firm value only when both management and auditors adopt the appropriate mindset to utilise the information generated by AI technology (Commerford et al;. 2022; Estep et al. 2024). Second, as a relatively nascent computer-based technology, AI remains immature and may produce errors and biased outcomes (Munoko et al. 2020; Osoba, Welser IV, and Welser 2017). Moreover, lenders may struggle to observe, measure, and interpret the performance of a borrower's AI capacity due to the highly technical and complex nature of these technologies (Deloitte 2022; Kim et al. 2018; Zhang, Cho, and Vasarhelyi 2022). Consequently, if lenders do not perceive a borrower's AI capacity as a reliable source of future cash flow, they may not lower loan prices for borrowers with high AI capacity. In sum, whether a borrower's AI capacity leads to lower cost of debt remains an empirical question. Accordingly, we state the following hypothesis in the null form:

***H1: Ceteris paribus, a borrower's AI capacity is not associated with its cost of debt.***

## 3. RESEARCH DESIGN AND SAMPLE SELECTION

### 3.1 Measuring AI capacity

A firm's AI capacity generally comprises three key components: AI technology (e.g., data and algorithms), AI-related infrastructure (e.g., computer hardware), and AI-skilled workers (Cen et al. 2024). AI-related infrastructure at the firm level is not publicly accessible, and many components, such as computers or servers, may also support traditional data processing technologies. This overlap makes it difficult to distinguish AI-specific investments from non-AI-related ones. On the other hand, AI technology can be directly measured using AI patent data from the Artificial Intelligence Patent Dataset (AIPD) (Chen and Srinivasan 2024). However, AI patent data, akin to the concept of "finished goods" in managerial accounting, only captures the visible outcomes of a firm's AI capacity. It does not account for a firm's "AI-related raw materials" or "AI-related work-in-process" inventory, thereby overlooking significant components of firms' total AI capacity. In addition, AI patents primarily emphasize innovation rather than operational deployment (Giczy, Pairolero, and Toole 2022), not fully capturing firm-wide investments in AI. By contrast, AI-skilled workers represent a firm's sustained and strategic AI capacity because their expertise and functions interact holistically with the foundational AI infrastructure, broadly reflecting the company's ability to develop and deploy AI (Law and Shen 2024) in the business. Therefore, we argue that AI-skilled workers represent a crucial input to AI capacity and use the number of AI-skilled workers to measure a company's overall commitment to various aspects of AI technologies.

Following prior studies (Cen et al. 2024; Raj and Seamans 2024), we use Revelio Labs to obtain relevant information in constructing AI-skilled worker intensity at firm-year level.[4] Revelio Labs is a leading provider of human capital database, collecting employment-related information at both firm and individual levels from public platforms such as LinkedIn and Indeed. Revelio Labs provides the largest and most dynamic workforce data with more than 4.5 million companies located in 5.2 thousand cities and states and over 1.1 billion individual profiles globally. The resume text is standardized to deliver a normalized view of all roles, skills, and activities (wrds-www.wharton.upenn.edu). Moreover, the data aggregation process does not rely on information disclosed by companies, thus eliminating the voluntary disclosure bias.

[4] Prior studies (e.g., Babina et al. 2024; Fedyk et al. 2022) use job posting data from alternative databases to capture AI-related human capital. However, job postings data primarily reflect a firm's intent to invest in AI rather than its actual investment (Acemoglu, Autor, Hazell and Restrepo 2022).

To achieve comprehensive and balanced coverage of firm-level human capital data across industries and years, we utilise the Individual Resume dataset spanning 2010 to 2019.[5] First, we collect employment records of individuals working in U.S. companies with a Compustat company identifier (gvkey). For each record, we collect the individual's identifier, skills, start and end dates, company name and ID, job title, and job description. Employees are classified as AI-skilled workers if their job titles or descriptions contain AI-related keywords.[6] The number of AI-skilled workers and total workers are aggregated at the firm-year level. Specifically, for each firm, we construct monthly counts of AI and total employees based on employment start and end dates. We take the mean value across twelve months each year as the number of AI workers and total employees for that year. Finally, AI-skilled worker intensity (*AI Ratio*) is computed as the ratio of the number of AI employees to the total number of employees of the firm.

### 3.2 Model Specification

Our main hypothesis posits that firms' AI capacity may or may not influence their cost of debt. To test this hypothesis, we estimate the following regression model:

$$SPREAD_{i,t} = \alpha_0 + \alpha_1 \times AI\ Ratio_{j,t-1} + Loan\ Controls_{i,t} + Borrower\ Controls_{j,t-1} + \phi_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

5 Online platforms emerged in early 2000s, making it possible for Revelio to start collecting unstructured labor market data from various sources. Therefore, starting the sample period from 2010 ensures that the workforce information is well populated. Also, we only use the years through 2018 because the lag in individual resume updates could otherwise add noise to our measure. Our sample period is generally consistent with several recent papers in this line of research (e.g., Baker et al. 2024; Cai, Chen, Rajgopal, and Azinovic-Yang 2024; Law and Shen 2024; Liang, Lourie, Nekrasov, and Yoo 2024).
6 We follow Babina et al. (2024) and Fedyk et al. (2022) and use a list of 67 AI-related keywords to determine whether the job title and description indicate an AI-skilled worker. They use a methodical set of steps to classify AI-related keywords. The process begins with the identification of a foundational set of clear and specific AI skills, such as deep learning, natural language process. Then other skills that frequently appear together with the AI skills are captured through examining the Job Postings data. These secondary AI skill words are scored based on the relatedness to the core AI words and a refined list of 67 keywords is constructed using the scoring approach.

Where *SPREAD* is the natural logarithm of the all-in-drawn spread over the London Interbank Offered Rate (*LIBOR*) for loan $i$ issued to firm $j$ in year $t$. The loan spread reflects the rate of return required by lenders to compensate for the uncertainty they face. The variable of interest, *AI Ratio*, is the intensity of firm's AI-skilled workers defined above. The lagged value of the *AI Ratio* is employed to ensure that the borrower's AI capacity and strategy is observable to creditors before loan syndication. This approach also helps mitigate potential endogeneity concerns.

We follow prior studies in loan contracting (e.g., Bharath, Sunder, and Sunder 2008; Costello and Wittenberg-Moerman 2011; Graham, Li, and Qiu 2008) in selecting control variables. We control borrower characteristics that are commonly known to affect the loan interest rate. Borrower specific control variables include borrower size (*Size*), market-to-book value (*Mkbk*), tangible assets (*Tang*), borrower performance (*Roa*), R&D expense (*Rdat*), capital expenditure (*Capex*), leverage (*Levg*), and financial distress (*Zscore*). We expect borrower size, market-to-book value, borrower performance, tangible assets, and capital expenditure to be negatively related to our measures of cost of debt as larger, more profitable borrowers with higher growth potential are generally more stable and exhibit stronger cash flows (Berk 1995; Sheneman 2017). Therefore, they receive favorable terms in loan deals including a lower cost of debt financing. A borrower's financial health, measured by its Z-score, should be negatively associated with the cost of debt, as financially healthy firms have a lower default risk (Sheneman 2017). Borrower leverage is expected to have a positive relationship with the cost of debt, as higher leverage indicates greater financial risk, prompting lenders to demand a higher rate of return (Plumlee et al. 2015). To identify the distinct effects of AI workforce, we include research and development expenditure scaled by total assets (*Rdat*) and capital expenditure scaled by total assets (*Capex)* to control the effects of non-AI related investments used to support AI workforce. We do not predict the direction of the effect of a borrower's *Rdat* on cost of debt, as R&D investments can have a mixed impact (Eberhart, Maxwell, and Siddique 2008): lenders may view a borrower's R&D activities as indicators of both risk and potential growth (Ma, Novoselov, Stice, and Zhang 2024). In addition, we include S&P Global Ratings credit rating, borrower, and year fixed effects to control for the time-invariant borrower credibility and temporal macroeconomic conditions, respectively. Finally, loan type and loan purpose indicators are included to account for variations in the cost of debt across different types of loans (Kim, Song, and Zhang 2011; Sheneman 2017; Valta 2012). All borrower characteristics are measured in the year before loan syndication. Second, we include in Equation (1) a set of loan-specific control variables that can influence firms' cost of debt, including loan size (*Lloansize*), the maturity of the loan (*Lmat*), total number of covenants (*Total_cov*), reputable lead lender (*Rep2*), relationship lending (*Rel_loans*), whether the loan is secured (*Secured*), and whether the loan is syndicated (*Syndicated*). Prior research finds that banks impose lower interest rates for loans with shorter maturity, larger amounts, and fewer covenants (Graham et al. 2008; Smith and Warner 1979), and that banks charge higher rates for loans with collateral requirement (Bharath, Dahiya, Saunders, and Srinivasan 2011). In addition, syndication structure may also influence the loan spread and the number of financial covenants included in the loan agreement (e.g., Sufi 2007). See the Appendix A for details on variable definitions.

### 3.3 Sample selection and summary statistics

We construct our sample using data from three vendors. We obtain workforce data from Revelio Lab, loan data from DealScan, and borrower firm information from Compustat. As we discuss in the previous section regarding constructing the measure of AI capacity, we exploit all Revelio individual resume database from 2010 to 2018 and construct AI-skilled worker intensity at firm-year level for companies with a GVKEY in Compustat. We obtain loans issued from years

2011 to 2019 from Dealscan and use the Dealscan_Compustat Linking Database provided by Michael Roberts to match the loan data with the Compustat data to form our main analysis sample. Our primary sample contains 11,195 loan facilities by 2,227 borrowers. Sample sizes for further empirical tests vary due to additional data requirements.

In Table 1, we present the descriptive statistics of our primary sample. Panel A lists the number of loans issued in each year from 2011 to 2019 and shows a balanced distribution across the nine years of sample period. Panel B reports the summary statistics for our main test variable, the AI-skilled worker intensity (*AI ratio*), and our dependent variables, along with control variables for loans and borrowers. This table show that on average, 0.8 percent of the workforce of a borrower firm are AI-skilled employees. The mean (standard deviation) of loan spread in our sample is 223.878 (140.401), consistent with prior studies. The summary statistics of control variables are also consistent with recent studies of similar sample periods (e.g., Fang, Li, Xin, and Zhang 2016; Kim et al. 2018). Panel C reports the Pearson correlations across the variables, which indicate that our AI capacity measure is significantly and negatively correlated with bank loan spreads. This suggests that firms' AI capacity may reduce their default risk and the uncertainty faced by lenders. Consistent with prior studies, our control variables are systematically associated with both our cost of debt proxies and AI capacity measure.

[Table 1]

## 4. EMPIRICAL RESULTS

### 4.1 Main Test

Table 2 presents the estimation results for the effect of borrower capacity on the cost of debt. The findings reveal a negative and significant relationship between a borrower's AI-skilled worker intensity and its loan spread (*coefficient=-2.299, t-statistics =-4.207*), consistent with the expectation that a borrower's AI capacity reduces default risk and lender uncertainty, leading to lower cost of debt. The economic magnitude is also significant. For every 1 percent increase in AI ratio, the loan spread is 2.3% lower and equivalent to 5 basis points of the average loan spread of the sample.[7]

Regarding the relationship between loan characteristics and cost of debt, our results indicate that larger loans, loans with more covenants, and loans syndicated by reputable and relationship lenders are associated with lower loan spreads, consistent with prior literature (e.g., Bhrath et al. 2008). Both loan maturity and secured loans are positively associated with higher loan spreads. Regarding the relationship between borrower-characteristics and cost of debt, the results indicate that larger borrowers (*Size*), financially healthy borrowers (*Zscore*), and those with better performance (*ROA*), and higher capital expenditure (*Capxat*) have lower costs of debt compared to their peers, as anticipated.

[Table 2]

### 4.2 Cross-Sectional Analyses

#### 4.2.1. Product market competition

As previously discussed, AI technology may enhance firm performance and reduce default risk—thereby lowering the cost of debt—through strengthening a borrower's competitive position in product markets. Borrowers are consistently exposed to cash flow and competitive risks (Bolton and Scharfstein 1990; Irvine and Pontiff 2009) and their creditors face greater cash flow

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[7] The reduction in spread is calculated as 1- exp (-2.299*0.01); The equivalent basis points is calculated as 0.023*223=5.129.

uncertainty (Carpenter and Petersen 2002; Holmstrom 1989) when product market competition is high. If the effect of AI capacity on cost of debt is through its positive impact of product innovation, the benefits of AI technology are expected to be most significant for borrowers with greater product market competition or borrowers operating in highly competitive markets. To test this conjecture, we divide our main sample into two sub-samples based on the level of product market competition they face. To capture the intensity of product market competition, we use Hoberg, Phillips, and Prabhala's (2014) product fluidity measure, which reflects competition arising from product substitutability (Karuna 2007), and the Herfindahl-Hirschman Index (*HHI*), which quantifies sales concentration of an industry. The results reported in Table 3 show that in the sample of borrowers with product fluidity index greater than industry median (column (1): *Product Fluid H*), high AI compacity is associated with a lower cost of debt (*coefficient = -2.462, t-statistics=-3.352*). In contrast, in the sample of borrowers with low product fluidity index (column (2)), there is no significant relationship between *AI Ratio* and cost of debt. The difference in the coefficients on *AI Ratio* between the high and low product fluidity sample is statistically significant at the 10% level. However, when we use *HHI* to split the sample, we do not find significant difference in the coefficients on *AI Ratio* between high and low *HHI* samples. The different results using different measures of product market competition might be because *HHI* only captures industry concentration rather than competitive pressure due to product substitution.

[Table 3]

#### 4.2.2. Investment Commitment

AI technology alone may not necessarily guarantee the success of a firm's AI investments because the realization of the potential benefits of AI technologies also depends on whether a firm possesses sufficient resources and strong commitment to utilize AI technology (Estep et al. 2024;

Higgins 2005). To explore whether creditors' pricing of AI capacity depends on a borrower's investment commitment, we analyze the effect of AI capacity on cost of debt for a sample of borrowers with high and low commitment to investment in future growth. We use R&D expenditures and capital expenditures as a measure of a borrower's commitment to investment to support AI capacity as they represent a borrower's long-term commitment to invest in intangibles assets for firm growth (Hunter, Webster, and Wyatt 2012). The results in Table 4 show that in the sample of borrowers with R&D expenditures greater than industry median (column (1)), high AI capacity borrowers incur lower cost of debt (*coefficient = -3.365, t-statistics =-4.136*), while the coefficient on *AI ratio* is negative and yet insignificant in the sample of borrowers with low R&D expenditures (column (2)). The difference in the coefficients between the two subsamples are statistically significant at the 5% level. The results are similar when using capital expenditures to split the sample. These results imply that creditors may only price AI capacity when a borrower exhibits strong commitments to support AI technologies.

[Table 4]

#### 4.2.3 Alternative Channel for the Effect of AI Technology on Cost of Debt

Although our evidence suggests that AI capacity might reduce credit risk for borrowers through its positive impact on product innovations, AI technology can also reduce cost of debt because it enhances a borrowers' financial reporting quality and reduces information asymmetry through improved data collection and analysis capabilities (e.g., Anantharaman et al. 2023; Bao et al. 2019; Ding et al. 2020). For example, Bao et al. (2019) and Ding et al. (2020) find that using machine learning can effectively improve irregularity detection and accounting estimates. These findings imply that AI capacity may lead to a more robust financial reporting system and reduce uncertainty and default risk for lenders thereby lowering firms' cost of debt (Bharath et al. 2008;

Costello and Wittenberg-Moerman 2011; Fang et al. 2016). We conduct another cross-sectional test to test this conjecture.

If AI technology lowers cost of debt by improving borrowing firms' information quality, we expect AI capacity has a more pronounced effects on cost of debt in firms with poor information environments. We use analysts forecast dispersion, analyst coverage, and the availability of credit rating as proxies for a borrower's information environment. Analyst forecast dispersion reflects the information uncertainty faced by analysts (Barron, Kim, Lim, and Stevens 1998; Lee, Pandit, and Willis 2013) while analyst coverage mitigates the information asymmetry between firms and outsiders (Hong, Lim, and Stein 2000). Borrowers with credit rating typically face lower information asymmetry and have better information environment in credit markets (Sufi 2007). We estimate equation (1) for a sample of borrowers with high and low analyst dispersion and coverage and with and without credit ratings. The results in Table 5 show that there is no significant difference in the coefficients on *AI Ratio* between the sample of borrowers with poor and good information environments, suggesting that the effect of AI capacity on cost of debt is not through its impact on a borrower's information environments.

[Table 5]

## 5. ADDITIONAL ANALYSIS

### 5.1 AI Capacity and Future Credit Risk

To further validate our main finding that a borrower's AI capacity mitigates default risk and, consequently, lowering its cost of debt, we investigate whether AI capacity can reduce a borrower's future credit risk. Specifically, we examine whether there is a negative association between a borrower's AI capacity and its expected default frequency (*EDF*), as well as the likelihood of future credit rating downgrades. These two variables serve as proxies for firms' future credit risk (Alldredge, Chen, and Luo 2022; Bharath and Shumway 2008). Table 6 reports that a borrower's AI capacity is significantly associated with lower future EDF and fewer future credit rating downgrades, confirming our conjecture that lenders lower cost of debt for high AI capacity borrowers because lenders believe that AI technology can reduce a borrower's default risk.

[Table 6]

**5.2 Alternative Measures of AI Capability**

Brynjolfsson et al. (2019) highlight an "implementation lag" between the adoption of AI technologies within an organisation and the realisation of their benefits, indicating that the effects of AI technology unfold gradually over time. Accordingly, instead of measuring AI-skilled worker intensity one year prior to loan initiation, we use the same variable measured two years prior as an alternative proxy for AI capacity and rerun our main analysis. Furthermore, as some studies use the total number of AI-skilled workers (e.g., Cen et al. 2024) rather than the AI-skilled worker intensity to measure AI capacity, we also rerun our main analysis using the total number of AI-skilled workers. The results in Table 7 show that using both lagged measures yield results consistent with our main findings in Table 2. In addition, we use forward-looking *AI Ratios* to predict cost of debt and find that one-year ahead (column 3) and two-year ahead *AI Ratios* (column 4) are not related to cost of debt, suggesting that the documented negative relationship between *AI Ratios* and cost of debt is not due to spurious relationship between the two variables.

[Table 7]

**5.3. AI Capacity and Non-pricing Contracting Terms**

Lenders often incorporate additional non-pricing terms in loan agreements with borrowers to strengthen their control rights and mitigate agency costs. For example, imposition of financial covenants acts as important "trip wires" to restrict a borrower's behaviour and transfer control rights to creditors when borrower performance deteriorates (e.g., Aghion and Bolton 1992; Dewatripont and Tirole 1994; Dichev and Skinner 2002; Dyreng et al. 2017). Lenders may require collateral to monitor borrowers and reduce potential losses in the event of default (Graham et al. 2008; Rajan and Winston 1995). Additionally, if lenders perceive a higher degree of default risk and require greater monitoring of borrowers, they tend to shorten loan maturity (Barclay and Smith 1995; Ortiz-Molina and Penas 2008; Wang, Chiu, and King 2020) and reduce loan size (Beatty, Ramesh, and Weber 2002; Booth 1992). We therefore use the number of financial covenants, collateral requirement, loan maturity, and loan size as dependent variables and estimate the effect of AI capacity on these non-pricing terms. Table 8 indicates that a borrower's AI capacity does not affect these non-pricing terms. These results suggest that despite being willing to lower the cost of debt for borrowers with high AI capacity, lenders remain cautious due to the uncertainties associated with AI technology itself and are therefore unwilling to forgo using non-pricing terms as additional monitoring devices.[8]

[Table 8]

## 6. CONCLUSION

As we enter the age of Artificial Intelligence, there has been a significant surge in the adoption and integration of AI technologies across various industries and organisations. Both

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[8] A large volume of empirical studies show that when a borrower exhibits lower (higher) credit risk, creditors may offer more (less) favorable pricing terms (i.e., lower cost of debt) and non-pricing terms (i.e., imposing fewer (more) debt covenants, wavering (requiring) collateral, and offering larger (smaller) loans and loans with longer (shorter) maturity) at the same time (e.g., Bharath et al. 2008; Costellos and Wittenberg Moerman 2011; Kim et al. 2018; Graham et al. 2008).

industry professionals and academics recognise the immense potential of AI to drive knowledge creation and enhance productivity (Babina et al. 2024; Brynjolfsson et al. 2019). This study seeks to further explore the value of AI capacity at the firm level by providing empirical evidence on how AI technologies influence firms' external financing in the debt market. Using a unique human capital database from Revelio Labs, we document that a borrower' AI capacity, on average, positively impact its external financing by reducing the cost of debt. Furthermore, we demonstrate that the effect of AI capacity on cost of debt is more pronounced among borrowers facing higher product market competition and borrowers with stronger commitment to invest in intangible assets. Our study is the first to provide empirical evidence on the impact of AI technology on the debt market and bank lending behaviour. However, it faces several limitations. First, our measurement of AI capacity may not fully capture the precise AI-related investments made by firms. We identify AI-skilled workers through a keyword search, but it is possible that other personnel contributing to AI development might hold alternative or more general titles. Future studies could explore more precise methods to measure firm-level AI capacity. Additionally, while we examine the channels through which AI affects the cost of debt, we do not differentiate the effects of various types of AI technologies. Further research in this area would be valuable.

## Appendix A

| Variable | Definitions |
|---|---|
| **Dependent, independent, and control variables** | |
| *SPREAD* | Natural logarithm of all-in-drawn spread measured by the basis points above the LIBOR for loans. |
| *AI Ratio* | The ratio of employees with AI skills to the total number of employees. |
| *LogAI* | Natural logarithm of 1 plus the total number of employees with AI skills. |
| *Lag2_AI Ratio* | Average *AI Ratio* across two years before the loan issue year. |
| *Size* | Natural logarithm of total assets. |
| *Mkbk* | Market to book ratio. |
| *Tang* | Tangible assets divided by total assets (PPENT/AT). |
| *Roa* | Return on assets (NI/AT). |
| *Rdat* | R&D expense divided by total assets (XRD/AT). |
| *Capex* | Capital expenditure is divided by total assets (CAPX/AT). |
| *Zscore* | Altman's bankruptcy Z-score (1.2 × WCAP/AT + 1.4 × Return on Equity/AT + 3.3 × EBIT/AT + 0.6 × (PRCC_F × CSHO)/LT + SALE/AT). |
| *Levg* | Leverage which is computed as the borrower's book value of total debt divided by market value of equity ((DLTT+ DLC)/(PRCC_F × CSHO)). |
| *Rep2* | Equals 1 if the loan syndicate contains at least one reputable lead lender, and 0 otherwise. Reputable lead lender is defined as the lead lender that has a market share of syndicated loans greater than 2% in the year before the current deal. |
| *Rel_loans* | Number of loans a borrower has borrowed from the same lead lender in the past 5 years before the current deal. |
| *Total_cov* | Total number of covenants in a loan deal. |
| *Syndicated* | Equals 1 if the loan is a syndicated loan, and 0 otherwise. |
| *Secured* | Equals 1 if the loan deal contains a collateral requirement, and 0 otherwise. |
| *Lloansize* | Natural logarithm of loan amount. |
| *Lmat* | Natural logarithm of loan maturity. |
| *leveraged_loan* | Equals 1 if a firm's credit rating is below BBB or it does not have a credit rating, and 0 otherwise. |
| *Revolver* | Equals 1 if a loan deal contains at least one revolver loan, and 0 otherwise. |
| **Other test variables** | |
| *Product fluid_H* | Equals 1 if a company's product market fluidity is greater than the 2-digit industry sample median, and 0 otherwise. Product market fluidity is a measure of the product market threat developed by Hoberg, Phillips, and Prabhala (2014). |

**Appendix A (continued)**

| Variable | Definitions |
|---|---|
| *Product fluid_L* | Equals 1 if a company's product market fluidity is lower than the 2-digit industry sample median and 0 otherwise. Product market fluidity is a measure of the product market threat developed by Hoberg, Phillips, and Prabhala (2014). |
| *HHI_H* | Equals 1 if a company's *HHI* is higher than the 2-digit industry sample median and 0 otherwise. |
| *HHI_L* | Equals 1 if a company's *HHI* is lower than the 2-digit industry sample median and 0 otherwise. |
| *EDF* | Expected default frequency in each month. |
| *EDF12* | Average expected default frequency over 12 months before the loan initiation date. |
| *S&PDG* | Equals 1 if S&P Global Ratings downgrades a company's credit rating from the credit rating 6 months ago and 0 otherwise. |
| *Disp_H* | Equals 1 if the dispersion of analysts' forecast of a company's EPS is greater than the sample median, and 0 otherwise. |
| *Disp_L* | Equals 1 if the dispersion of analysts' forecast of a company's EPS is lower than the sample median, and 0 otherwise. |
| *Coverage_H* | Equals 1 if the number of analysts following a company is greater than the sample median, and 0 otherwise. |
| *Coverage_L* | Equals 1 if the number of analysts following a company is lower than sample median, and 0 otherwise. |
| *Not rated* | Equals 1 if a company does not have an S&P credit rating, and 0 otherwise. |

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## Table 1 Descriptive Statistics

**Panel A:** Loan insurance yearly distribution

| loan issuance year | Freq. | Percent (%) | Cumulative (%) |
|---|---|---|---|
| 2011 | 1,397 | 12.48 | 12.48 |
| 2012 | 1,158 | 10.34 | 22.82 |
| 2013 | 1,384 | 12.36 | 35.19 |
| 2014 | 1,336 | 11.93 | 47.12 |
| 2015 | 1,260 | 11.26 | 58.37 |
| 2016 | 1,152 | 10.29 | 68.66 |
| 2017 | 1,287 | 11.50 | 80.16 |
| 2018 | 1,198 | 10.70 | 90.86 |
| 2019 | 1,023 | 9.140 | 100.00 |
| Total | 11,195 | 100.00 | |
| Number of firms: | 2,227 | | |

**Panel B:** Summary statistics

| **Variables** | **N** | **Mean** | **Std. Dev.** | **p25** | **p50** | **p75** |
|---|---|---|---|---|---|---|
| *SPREAD* | 11,195 | 223.878 | 140.401 | 125 | 175 | 275 |
| *Total_cov* | 11,195 | 1.806 | 2.506 | 0 | 0 | 3 |
| *AI Ratio* | 11,195 | 0.008 | 0.013 | 0.001 | 0.004 | 0.009 |
| *Size* | 11,195 | 8.121 | 1.591 | 6.985 | 8.108 | 9.257 |
| *Mkbk* | 11,195 | 1.806 | 1.009 | 1.187 | 1.501 | 2.039 |
| *Tang* | 11,195 | 0.294 | 0.251 | 0.091 | 0.204 | 0.451 |
| *Roa* | 11,195 | 0.036 | 0.090 | 0.012 | 0.041 | 0.074 |
| *Rdat* | 11,195 | 0.017 | 0.036 | 0 | 0 | 0.0168 |
| *Capex* | 11,195 | 0.052 | 0.057 | 0.018 | 0.034 | 0.063 |
| *Levg* | 11,195 | 0.290 | 0.208 | 0.150 | 0.266 | 0.397 |
| *Zscore* | 11,195 | 2.984 | 2.060 | 1.684 | 2.651 | 3.954 |
| *Rep2* | 11,195 | 0.652 | 0.476 | 0 | 1 | 1 |
| *Rel_loans* | 11,195 | 1.781 | 1.632 | 1 | 1 | 3 |
| *Secured* | 11,195 | 0.475 | 0.499 | 0 | 0 | 1 |
| *Syndicated* | 11,195 | 0.957 | 0.202 | 1 | 1 | 1 |
| *Lloansize* | 11,195 | 19.666 | 1.342 | 18.826 | 19.742 | 20.618 |
| *Lmat* | 11,195 | 3.928 | 0.507 | 3.951 | 4.094 | 4.094 |
| *leveraged_loan* | 11,195 | 0.262 | 0.440 | 0 | 0 | 1 |
| *Revolver* | 11,195 | 0.575 | 0.494 | 0 | 1 | 1 |

**Table 1 (continued)**

**Panel C: Pearson Correlation**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | *Spread* | 1 | | | | | | | | | |
| 2 | *AI Ratio* | -0.052 | 1 | | | | | | | | |
| | | 0.000 | | | | | | | | | |
| 3 | *Size* | -0.376 | 0.059 | 1 | | | | | | | |
| | | 0.000 | 0.000 | | | | | | | | |
| 4 | *Mkbk* | -0.152 | 0.223 | -0.149 | 1 | | | | | | |
| | | 0.000 | 0.000 | 0.000 | | | | | | | |
| 5 | *Tang* | -0.015 | -0.208 | 0.155 | -0.213 | 1 | | | | | |
| | | 0.122 | 0.000 | 0.000 | 0.000 | | | | | | |
| 6 | *ROA* | -0.281 | 0.027 | 0.123 | 0.325 | -0.131 | 1 | | | | |
| | | 0.000 | 0.004 | 0.000 | 0.000 | 0.000 | | | | | |
| 7 | *Rdat* | 0.000 | 0.413 | -0.128 | 0.338 | -0.285 | 0.003 | 1 | | | |
| | | 0.981 | 0.000 | 0.000 | 0.000 | 0.000 | 0.746 | | | | |
| 8 | *Capxat* | 0.002 | -0.091 | -0.023 | -0.020 | 0.663 | -0.081 | -0.138 | 1 | | |
| | | 0.842 | 0.000 | 0.017 | 0.037 | 0.000 | 0.000 | 0.000 | | | |
| 9 | *Levg* | 0.202 | -0.113 | 0.119 | -0.057 | 0.161 | -0.156 | -0.200 | 0.047 | 1 | |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | |
| 10 | *Zscore* | -0.258 | 0.108 | -0.164 | 0.579 | -0.286 | 0.552 | 0.196 | -0.119 | -0.475 | 1 |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | |
| 11 | *Total_cov* | 0.112 | -0.008 | -0.248 | 0.004 | -0.104 | -0.030 | 0.001 | -0.066 | 0.029 | 0.013 |
| | | 0.000 | 0.430 | 0.000 | 0.715 | 0.000 | 0.002 | 0.936 | 0.000 | 0.002 | 0.161 |

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 12 | *Rep2* | -0.193 | 0.011 | 0.265 | 0.013 | -0.057 | 0.084 | -0.034 | -0.077 | 0.094 | -0.015 |
| | | 0.000 | 0.263 | 0.000 | 0.171 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.106 |
| 13 | *Rel_loan* | -0.236 | -0.024 | 0.382 | -0.049 | 0.067 | 0.021 | -0.113 | -0.005 | 0.226 | -0.145 |
| | | 0.000 | 0.011 | 0.000 | 0.000 | 0.000 | 0.025 | 0.000 | 0.633 | 0.000 | 0.000 |
| 14 | *Secured* | 0.472 | -0.039 | -0.291 | -0.120 | -0.061 | -0.167 | -0.003 | -0.035 | 0.195 | -0.164 |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.723 | 0.000 | 0.000 | 0.000 |
| 15 | *Syndicated* | 0.035 | -0.018 | -0.067 | 0.008 | -0.055 | 0.015 | -0.003 | -0.037 | 0.003 | 0.046 |
| | | 0.000 | 0.061 | 0.000 | 0.416 | 0.000 | 0.104 | 0.784 | 0.000 | 0.765 | 0.000 |
| 16 | *Lloansize* | -0.402 | 0.056 | 0.605 | 0.025 | 0.053 | 0.147 | -0.055 | -0.002 | 0.099 | -0.020 |
| | | 0.000 | 0.000 | 0.000 | 0.008 | 0.000 | 0.000 | 0.000 | 0.871 | 0.000 | 0.037 |
| 17 | *Lmat* | 0.166 | -0.025 | -0.141 | -0.014 | -0.043 | 0.019 | -0.018 | -0.038 | 0.072 | 0.004 |
| | | 0.000 | 0.008 | 0.000 | 0.147 | 0.000 | 0.050 | 0.057 | 0.000 | 0.000 | 0.706 |
| 18 | *leveraged loan* | 0.249 | -0.071 | 0.033 | -0.165 | 0.063 | -0.140 | -0.108 | 0.033 | 0.359 | -0.287 |
| | | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 |
| 19 | *Revolver* | -0.300 | -0.023 | -0.048 | 0.005 | 0.089 | 0.037 | -0.018 | 0.085 | -0.150 | 0.095 |
| | | 0.000 | 0.014 | 0.000 | 0.621 | 0.000 | 0.000 | 0.059 | 0.000 | 0.000 | 0.000 |

| | | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|---|---|---|---|
| 11 | *Total_cov* | 1 | | | | | | | | |
| | | | | | | | | | | |
| 12 | *Rep2* | -0.019 | 1 | | | | | | | |
| | | 0.042 | | | | | | | | |
| 13 | *Rel_loan* | -0.038 | 0.239 | 1 | | | | | | |
| | | 0.000 | 0.000 | | | | | | | |
| 14 | *Secured* | 0.367 | -0.081 | -0.065 | 1 | | | | | |
| | | 0.000 | 0.000 | 0.000 | | | | | | |
| 15 | *Syndicated* | 0.094 | 0.018 | 0.019 | 0.031 | 1 | | | | |
| | | 0.000 | 0.063 | 0.044 | 0.001 | | | | | |
| 16 | *Lloansize* | -0.097 | 0.325 | 0.363 | -0.194 | 0.020 | 1 | | | |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.036 | | | | |
| 17 | *Lmat* | 0.085 | 0.066 | -0.050 | 0.228 | 0.081 | -0.047 | 1 | | |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | | |
| 18 | *leveraged loan* | 0.167 | 0.062 | 0.044 | 0.279 | 0.046 | 0.007 | 0.106 | 1 | |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.466 | 0.000 | | |
| 19 | *Revolver* | 0.005 | 0.033 | 0.004 | -0.142 | 0.036 | -0.017 | 0.108 | -0.083 | 1 |
| | | 0.598 | 0.001 | 0.676 | 0.000 | 0.000 | 0.073 | 0.000 | 0.000 | |

This table provides yearly distribution of loan insurance in our main sample (Panel A), summary statistics (Panel B) and Pearson correlations (Panel C) for variables used in our estimations. In Panel C, the numbers below the Pearson correlation coefficients are the p-values of the correlation. See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution.

**Table 3 AI capacity and cost of debt**

| Dependent variable = | (1)<br>*$SPREAD_t$* |
|---|---|
| *$AI\ Ratio_{t-1}$* | -2.299*** |
| | [-4.207] |
| *$Size_{t-1}$* | -0.037** |
| | [-2.382] |
| *$Mkbk_{t-1}$* | -0.017 |
| | [-1.546] |
| *$Tang_{t-1}$* | 0.131 |
| | [1.555] |
| *$Roa_{t-1}$* | -0.250*** |
| | [-2.827] |
| *$Rdat_{t-1}$* | 0.488 |
| | [0.990] |
| *$Capex_{t-1}$* | -0.347** |
| | [-2.252] |
| *$Levg_{t-1}$* | 0.197*** |
| | [4.103] |
| *$Zscore_{t-1}$* | -0.019*** |
| | [-2.816] |
| *$Total\_cov_t$* | -0.015*** |
| | [-5.501] |
| *$Rep2_t$* | -0.036*** |
| | [-2.815] |
| *$Rel\_loans_t$* | -0.025*** |
| | [-5.116] |
| *$Secured_t$* | 0.191*** |
| | [11.922] |
| *$Syndicated_t$* | 0.101*** |
| | [3.204] |
| *$Lloansize_t$* | -0.068*** |
| | [-10.366] |
| *$Lmat_t$* | 0.070*** |
| | [5.504] |
| *$Leverage\_loan_t$* | 0.556*** |
| | [2.900] |
| *$Revolver_t$* | -0.171*** |
| | [-19.822] |
| *Constant* | 6.823*** |
| | [43.312] |
| Loan purpose fixed effects | Yes |
| Firm, year, and credit rating fixed effects | Yes |
| Observations | 11,195 |
| Adjusted R-square | 0.778 |

Notes: This table presents the results for the effects of AI capacity on cost of debt. The dependent variable is *SPREAD* and the independent variable is the *AI Ratio* one year before loan initiation. See Appendix A for variable definitions. Standard errors are clustered at the firm-year level with robust and clustered t-statistics in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.

**Table 3 The Effect of AI Capacity on Cost of Debt Conditioning on Product Market Competition**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable = $SPREAD_t$ | *Product Fluid_H* | *Product Fluid_L* | *HHI_H* | *HHI_L* |
| ***AI Ratio$_{t-1}$*** | **-2.462***** | **-0.104** | **-2.043**** | **-1.728**** |
| | **[-3.352]** | **[-0.092]** | **[-1.992]** | **[-2.396]** |
| Controls variables | Yes | Yes | Yes | Yes |
| Loan purpose Fixed Effects | Yes | Yes | Yes | Yes |
| Credit rating fixed effects | Yes | Yes | Yes | Yes |
| Firm, year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 4,698 | 5,072 | 5,609 | 5,586 |
| Adjusted R-square | 0.781 | 0.795 | 0.777 | 0.795 |
| T-stats of the coefficient difference between *H* and *L* | | **-1.75** | | -0.25 |

Notes: This table presents the results for the moderating effects of product market competition on the relationship between AI capacity and cost of debt. The dependent variable is *SPREAD*. The independent variable of interest is lagged *AI Ratio*. Columns (1) and (2) present the estimation results for the subsamples with the Hoberg et al. (2014) product market fluidity index above 2-digit SIC industry median (*Product Fluid H)* or below 2-digit SIC industry median *(Product Fluid L)*. Columns (3) and (4) present the estimation results for the subsamples with industry concentration above the sample median (*HHI_H)* or below the sample median (*HHI_L*). See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution. Standard errors are clustered at the firm-year level with robust and clustered t-statistics provided in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.

**Table 4 The Effect of AI Capacity on Cost of Debt Conditioning on Investment Commitment**

| Dependent variable = $SPREAD_t$ | (1) *Rdat_H* | (2) *Rdat_L* | (3) *Capex_H* | (4) *Capex_L* |
|---|---|---|---|---|
| *AI Ratio*$_{t-1}$ | **-3.365*** ** | -1.053 | **-2.198*** ** | 2.252 |
| | [-4.136] | [-1.325] | [-4.091] | [1.065] |
| Controls | Yes | Yes | Yes | Yes |
| Loan purpose Fixed Effects | Yes | Yes | Yes | Yes |
| Credit rating fixed effects | Yes | Yes | Yes | Yes |
| Firm, year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 7,918 | 3,277 | 7,713 | 3,482 |
| Adjusted R-square | 0.787 | 0.770 | 0.778 | 0.839 |
| T-stats of the coefficient difference between *H* and *L* | **-2.03** | | **-2.04** | |

This table presents the results for the moderating effects of investment commitment on the relationship between AI capacity and cost of debt. The dependent variable is *SPREAD*. The independent variable of interest is lagged *AI Ratio*. Columns (1) and (2) present the estimation results for the subsamples with R&D expenditure above 2-digit SIC industry median (*Rdat H)* or below 2-digit SIC industry median *(Rdat L)*. Columns (3) and (4) present the estimation results for the subsamples with capital expenditure above 2-digit SIC industry median (*Capex_H)* or below the 2-Digit SIC industry median (*Capex_L*). See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution. Standard errors are clustered at the firm-year level with robust and clustered t-statistics provided in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.

**Table 5: The Effects of AI Capacity and Cost of Debt Conditioning on Borrowers Information Environment**

| Dependent variable = $SPREAD_t$ | (1) *Disp_H* | (2) *Disp_L* | (3) *Coverage_H* | (4) *Coverage_L* | (5) *Not Rated* | (6) *Rated* |
|---|---|---|---|---|---|---|
| ***AI Ratio*$_{t-1}$** | **-1.891** | **-1.409** | **-2.119*** ** | **-2.812** ** | **-2.058** ** | **-1.905** ** |
| | **[-1.066]** | **[-1.571]** | **[-3.337]** | **[-2.538]** | **[-2.208]** | **[-2.204]** |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Credit rating fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm, year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,907 | 4,897 | 5,422 | 5,773 | 5,427 | 5,723 |
| Adjusted R-square | 0.803 | 0.771 | 0.757 | 0.799 | 0.808 | 0.792 |
| T-stats of the coefficient difference between *H* and *L and Rated and Not Rated* | -0.24 | | -0.54 | | -0.12 | |

This table presents the results for the moderating effects of information quality on the relationship between AI capacity and cost of debt. The dependent variable is *SPREAD*. The independent variable of interest is lagged *AI Ratio*. Columns (1) and (2) present the estimation results for the subsamples with analyst forecast dispersion above sample median (*Disp H)* or below sample median *(Disp L)*. Columns (3) and (4) present the estimation results for the subsamples with analyst coverage above sample median (*Coverage_H)* or below the sample median (*Coverage_L*). Columns (5) and (6) present estimation results for the samples without credit ratings (*NotRated*) and with credit ratings (*Rated*). See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution. Standard errors are clustered at the firm-year level with robust and clustered t-statistics provided in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.

**Table 6: AI capacity and Future Credit Risk**

| Dependent variable = | (1)<br>*EDF12* | (2)<br>*EDF24* | (3)<br>*EDF36* | (4)<br>*S&P DG12* | (5)<br>*S&P DG24* | (6)<br>*S&P DG36* |
|---|---|---|---|---|---|---|
| *AI Ratio*$_{t-1}$ | **-1.147** | **-6.524**** | **-5.955**** | **-1.550***** | **-1.484***** | **-0.971***** |
| | [-0.348] | [-2.241] | [-2.300] | [-3.619] | [-3.910] | [-3.065] |
| *EDF12* | 0.909*** | 0.898*** | 0.911*** | | | |
| | [60.463] | [77.914] | [85.570] | | | |
| *Size*$_{t-1}$ | 0.528*** | 0.263** | -0.048 | 0.000 | 0.005 | -0.008 |
| | [3.570] | [2.023] | [-0.422] | [0.063] | [0.820] | [-1.554] |
| *Mkbk*$_{t-1}$ | -0.462*** | -0.702*** | -0.687*** | -0.027*** | -0.026*** | -0.024*** |
| | [-4.920] | [-8.776] | [-9.678] | [-4.640] | [-5.797] | [-6.662] |
| *Tang*$_{t-1}$ | 4.156*** | 5.761*** | 3.412*** | 0.123** | 0.255*** | 0.208*** |
| | [4.230] | [7.170] | [4.948] | [2.419] | [6.582] | [6.060] |
| *Roa*$_{t-1}$ | 8.735*** | 7.342*** | 3.992*** | -0.153*** | -0.032 | -0.040* |
| | [8.329] | [9.064] | [5.976] | [-3.021] | [-0.966] | [-1.675] |
| *Rdat*$_{t-1}$ | -2.853 | 0.025 | 1.397 | 0.301 | -0.112 | -0.255 |
| | [-1.028] | [0.011] | [0.653] | [0.938] | [-0.476] | [-1.563] |
| *Capex*$_{t-1}$ | 6.660*** | 1.949 | 0.663 | -0.132 | -0.052 | 0.005 |
| | [3.015] | [1.188] | [0.489] | [-1.406] | [-0.679] | [0.088] |
| *Levg*$_{t-1}$ | -0.773 | 1.676*** | 2.099*** | -0.061** | 0.041* | 0.032* |
| | [-1.227] | [3.339] | [4.753] | [-2.097] | [1.921] | [1.780] |
| *Zscore*$_{t-1}$ | -0.152** | -0.015 | 0.166*** | -0.008* | -0.002 | 0.001 |
| | [-2.036] | [-0.256] | [3.302] | [-1.885] | [-0.560] | [0.558] |
| *Total_cov*$_t$ | -0.022 | -0.031** | -0.016 | 0.002* | 0.003*** | 0.003*** |
| | [-1.081] | [-2.035] | [-1.152] | [1.854] | [4.291] | [3.817] |
| *Rep2*$_t$ | -0.354*** | -0.194*** | -0.028 | 0.016*** | 0.009*** | 0.003 |
| | [-4.804] | [-3.361] | [-0.584] | [3.798] | [3.166] | [1.459] |
| *Num_loans*$_t$ | 0.109*** | 0.139*** | 0.066*** | -0.010*** | -0.003*** | -0.001 |
| | [3.834] | [5.967] | [3.149] | [-6.275] | [-2.946] | [-0.612] |
| *Secured*$_t$ | 0.271*** | 0.110* | 0.061 | 0.030*** | 0.020*** | 0.012*** |
| | [3.287] | [1.763] | [1.103] | [5.871] | [5.823] | [4.094] |
| *Syndicated*$_t$ | 0.484*** | 0.167 | 0.026 | -0.011 | -0.010* | -0.019*** |
| | [3.544] | [1.328] | [0.221] | [-1.208] | [-1.729] | [-3.816] |
| *Lloansize*$_t$ | 0.001 | 0.019 | 0.040*** | 0.004*** | 0.001 | 0.001 |
| | [0.042] | [1.162] | [2.858] | [2.987] | [1.012] | [1.276] |
| *Lmat*$_t$ | 0.069 | 0.167*** | 0.133*** | -0.008*** | -0.009*** | -0.007*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | [1.447] | [4.546] | [4.380] | [-3.172] | [-5.081] | [-4.829] |
| *Leverage_loan$_t$* | 3.500 | -14.723*** | -8.057** | -0.303*** | -0.258*** | -0.205*** |
| | [1.399] | [-3.918] | [-2.156] | [-5.680] | [-5.380] | [-4.814] |
| *Revolver$_t$* | -0.032 | -0.055** | -0.015 | -0.007*** | -0.004*** | -0.002 |
| | [-0.882] | [-2.052] | [-0.653] | [-3.092] | [-2.708] | [-1.381] |
| Constant | -10.033*** | -9.339*** | -6.646** | 0.031 | -0.043 | 0.089 |
| | [-3.168] | [-3.151] | [-2.331] | [0.373] | [-0.687] | [1.546] |
| Loan purpose FEs (Lbo, takeover, corporate purpose) | Yes | Yes | Yes | Yes | Yes | Yes |
| Credit rating fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| firm, year-month fixed effects | Yes | Yes | Yes | yes | yes | Yes |
| Observations | 110,358 | 208,544 | 280,977 | 47,732 | 91,863 | 127,841 |
| Adjusted R-square | 0.699 | 0.687 | 0.687 | 0.225 | 0.180 | 0.156 |

This table presents results estimating the effects of AI capacity on firms' future credit risk. Columns (1), (2), and (3) present the estimation results using monthly Expected Default Frequency (*EDF*) as the dependent variable. The *EDF* is calculated starting one month after the initiation of each loan facility and is stacked over 12, 24, and 36 months respectively. Column (4), (5), and (6) present the estimation results using the monthly S&P credit rating downgrading (*S&PDG*) as the dependent variable. The *S&PDG* is calculated starting one month after the initiation of each loan facility and is stacked over 12, 24, and 36 months respectively. See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution. Standard errors are clustered at the firm-year level with robust and clustered t-statistics provided in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.

**Table 7 Alternative Measures of AI Capacity**

| Dependent variable = *$SPREAD_t$* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *$AI\ Ratio_{avg\ (t-2,\ t-1)}$* | -1.603*** | | | |
| | [-3.121] | | | |
| *$Log\_AI\_EE_{t-1}$* | | -0.013** | | |
| | | [-2.172] | | |
| *$AI\ Ratio_{t+1}$* | | | -0.973 | |
| | | | [-1.402] | |
| *$AI\ Ratio_{t+2}$* | | | | 0.025 |
| | | | | [0.020] |
| Controls | Yes | Yes | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes | Yes |
| credit rating fixed effects | Yes | Yes | Yes | Yes |
| Firm, year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 8,607 | 11,195 | 11,187 | 11,178 |
| Adjusted R-square | 0.797 | 0.778 | 0.778 | 0.778 |

This table presents the estimation results of our baseline analysis using alternative measures of AI capacity as the independent variable. *$AI\ Ratio_{avg\ (t-2)}$* is the average of *AI Ratio* in years *t-1* and *t-2*, where *t* is the year of loan syndication; *$Log\_AI\_EE_{t-1}$* is the natural logarithm of (1+total number of AI employees) in year *t-1*. *$AI\ Ratio_{t+1}$* and *$AI\ Ratio_{t+2}$* are *AI ratios* in year *t+1* and *t+2*, respectively, where *t* is the year of loan syndication. See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution. Standard errors are clustered at the firm-year level with robust and clustered t-statistics provided in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.

**Table 8 AI Capacity and Non-pricing Contracting Terms**

| VARIABLES | (1)<br>*Lloansize* | (2)<br>*Lmat* | (3)<br>*total_fcov* | (4)<br>*Secured* |
|---|---|---|---|---|
| ***AI Ratio$_{t-1}$*** | **-0.774** | **-0.018** | **0.949** | **-0.009** |
| | **[-0.502]** | **[-0.027]** | **[0.625]** | **[-0.015]** |
| *Size $_{t-1}$* | 0.347*** | -0.049*** | -0.147*** | -0.035** |
| | [8.769] | [-2.858] | [-3.433] | [-2.039] |
| *Mkbk $_{t-1}$* | 0.028 | -0.022* | -0.012 | -0.026** |
| | [1.008] | [-1.712] | [-0.468] | [-1.978] |
| *Tang $_{t-1}$* | -0.116 | -0.154 | 0.231 | 0.005 |
| | [-0.504] | [-1.385] | [0.951] | [0.052] |
| *Roa $_{t-1}$* | 0.243 | 0.197* | 0.126 | -0.010 |
| | [1.361] | [1.936] | [0.552] | [-0.106] |
| *Rdat $_{t-1}$* | -0.264 | -0.997 | -0.100 | -0.058 |
| | [-0.186] | [-1.309] | [-0.078] | [-0.085] |
| *Capex $_{t-1}$* | 0.750** | 0.207 | -0.932** | -0.514*** |
| | [2.188] | [1.024] | [-2.306] | [-2.659] |
| *Levg $_{t-1}$* | 0.085 | -0.006 | -0.139 | 0.132** |
| | [0.638] | [-0.094] | [-1.006] | [2.191] |
| *Zscore $_{t-1}$* | 0.035** | 0.015* | -0.025 | -0.008 |
| | [2.131] | [1.808] | [-1.374] | [-0.984] |
| *Total_Cov $_t$* | 0.031*** | -0.006* | | |
| | [4.839] | [-1.726] | | |
| *Rep2 $_t$* | 0.335*** | 0.094*** | 0.012 | -0.021 |
| | [9.665] | [5.627] | [0.401] | [-1.601] |
| *Rel_loans $_t$* | 0.111*** | -0.004 | 0.045*** | 0.006 |
| | [8.256] | [-0.659] | [5.101] | [1.332] |
| *Secured $_t$* | -0.054 | 0.238*** | 0.385*** | |
| | [-1.314] | [11.760] | [10.151] | |
| *Syndicated $_t$* | 0.293*** | 0.256*** | 0.153*** | -0.004 |
| | [4.075] | [6.073] | [3.388] | [-0.136] |
| *Lloansize $_t$* | | 0.031*** | 0.041*** | -0.001 |
| | | [4.969] | [4.674] | [-0.180] |
| *lmat $_t$* | 0.137*** | | 0.019 | 0.124*** |
| | [4.948] | | [0.899] | [12.205] |
| *Leveraged Loan $_t$* | 0.300 | -1.707*** | -0.071 | 0.503* |
| | [1.158] | [-3.924] | [-0.095] | [1.700] |
| *Revolver $_t$* | -0.080*** | 0.163*** | 0.081*** | -0.052*** |
| | [-3.002] | [13.696] | [5.523] | [-6.679] |
| *Constant* | 15.286*** | 3.209*** | 0.619 | 0.362** |
| | [42.183] | [18.713] | [1.532] | [2.142] |
| Loan purpose fixed effects | yes | yes | yes | yes |
| Credit rating fixed effects | yes | yes | yes | yes |
| Firm and year fixed effects | yes | yes | yes | yes |
| Observations | 11,195 | 11,195 | 11,195 | 11,195 |
| Adjusted R-square | 0.652 | 0.442 | 0.664 | 0.688 |

This table presents the results for the effects of AI capacity on non-pricing contracting terms. The dependent loan size (*Lloansize*), loan maturity (*Lmat*), total number of financial covenants (*Total_fcov*), and an indicator variable for secured loan (*Secured*), respectively. The independent variable of interest is the ratio of total number of AI employees to the total number of employees in one year before loan initiation (*AI Ratio*). See Appendix A for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution. Standard errors are clustered at the firm-year level with robust and clustered t-statistics provided in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is indicated by ***, **, and *, respectively, using two-tailed tests.