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Headwind or tailwind? How banks interpret borrowers' AI exposure

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Abstract

General-purpose technologies create large opportunities but make their distribution across firms difficult to assess in real time. We use banks as interpreters of the rise of generative AI by studying lender-specific probability-of-default (PD) estimates for private firms in four large euro-area economies. As public attention to AI rises after ChatGPT, banks lower assessed default risk for borrowers in highly AI-exposed industries by about 5%. The reassessment is weaker for labor-intensive firms and stronger among lenders with pre-existing industry expertise. Yet the favorable industry-level effect is accompanied by a systematic reordering within product markets: banks reassess firms with stronger pre-ChatGPT market positions less favorably relative to their competitors, compressing the risk advantage associated with market leadership. Credit allocation moves in the same direction, with market leaders experiencing relatively lower drawn and committed credit, more relationship exits, and fewer new lenders. The reordering also predicts subsequent bad-credit events beyond banks' consensus PDs. Internal bank assessments therefore provide a forward-looking measure of how generative AI is expected to reshape competitive risk.

JEL codes: D82, D83, G21, G32, O33.

Keywords: Artificial intelligence; generative AI; bank lending; credit risk; probability of default; industry specialization; relationship lending; technological change.

Non-Technical Summary

New general-purpose technologies create large economic opportunities, but they make the identity of winners and losers difficult to establish while the technology is still diffusing. Generative artificial intelligence (AI) is a clear case, and the difficulty arises at two levels. Whether an exposed industry gains at all is ambiguous: the technology may automate costly tasks and raise productivity, but it may equally allow a firm's product to be replicated more cheaply, compress its margins, or force its business model to be rebuilt. And even where an industry gains, the advantage need not accrue to the firms that lead it today. Established leaders may be best placed to exploit a new technology, because they control the data, customer relationships and organisational capital that make it valuable; equally, AI may cheapen precisely the activities on which their lead was built and lower the cost at which smaller rivals can compete.

Someone must form a view on both questions long before the answer is visible in firms' accounts. In Europe most firms are private and depend on bank credit, and banks assess borrowers continuously on the basis of expected future performance rather than realised outcomes alone. Each lending bank reports, for each borrower, its own internal estimate of the probability that the borrower defaults over the following year (the PD). That estimate is not a statistical by-product: it feeds loan origination and monitoring, credit limits, pricing and provisioning and, for banks using the internal ratings-based (IRB) approach, the calculation of risk-weighted assets. Bank PDs therefore record how the financial system reads an economy-wide technological development, and that reading has direct consequences for the allocation of credit. This paper asks how banks revised their assessments when AI became salient after the public release of ChatGPT in the fourth quarter of 2022.

We use AnaCredit, the harmonised credit register of the European System of Central Banks, which records euro area banks' credit exposures to firms above a €25,000 threshold. We study non-listed, non-financial borrowers in Germany, France, Italy and Spain at quar-

terly frequency between the first quarter of 2021 and the last quarter of 2024, matched to company accounts from Orbis; the sample contains roughly 6.8 million firm–bank–quarter observations. We measure how exposed a borrower’s industry is to AI using several established indices, most of which map the capabilities of AI systems onto the tasks and abilities used in different occupations, and one of which classifies industries by observed AI-related skills, innovation and use. We combine this predetermined exposure with a measure of how salient AI is in a given country and quarter, built from Google search intensity and views of AI-related Wikipedia pages. Both attention measures are flat until the third quarter of 2022 and rise sharply thereafter. Two features of the data do the analytical work. Because we observe the PD each lender assigns, we can compare the assessments that different banks make of the same borrower at the same moment, separating what is happening to the firm from how its lenders read it. And because we can locate each borrower among its direct competitors, we can compare how a single bank assesses differently positioned firms inside the same narrow product market in the same quarter.

Banks read AI exposure, on average, as a credit tailwind rather than a headwind. A one-standard-deviation rise in public attention to AI is associated with an assessed PD roughly 5% lower for borrowers in the most exposed quartile of industries than for other borrowers. The pattern is directionally consistent across five exposure measures and holds within continuing bank–firm relationships, so it reflects a re-rating of existing borrowers rather than a reshuffling of firms towards more lenient lenders. The favourable reassessment is not uniform. It is markedly weaker where production relies heavily on labour: assessed PD falls by roughly 7% for borrowers with below-median labour intensity but only about 3% for those above it. When labour is mainly an input, AI is chiefly a way of doing the same thing more cheaply; when labour is central to the business model, the same technology is as much a threat as a saving. The reassessment also depends on what the lender knows. Comparing banks that lend to the same firm in the same quarter, lenders with at least 10% of their pre-ChatGPT corporate portfolio in the borrower’s industry lower their assessment

of highly exposed borrowers by some 11–16% more per standard deviation of attention than non-specialist co-lenders, and they also move these borrowers towards the safer end of their own portfolios. Lenders with long bilateral relationships, by contrast, assess the same borrowers no differently from their co-lenders, either in levels or in the ordering of their portfolios. Knowledge of the borrower’s sector appears to matter more for interpreting a new technology than familiarity with the borrower itself.

The favourable industry-level view conceals a reordering inside those industries. We define a market as a country and four-digit industry cell, and rank each firm by its sales relative to its competitors in the three years before ChatGPT. Comparing firms that borrow from the same bank in the same market and quarter, we find that as AI attention rises by one standard deviation, the market leader’s assessed default risk rises by about 8% relative to the smallest firm in the same highly exposed market. The gap emerges after ChatGPT’s release and grows with a firm’s pre-shock position, reaching about 10% for firms in the top decile of their market. Leaders are not marked down in absolute terms; they also share in the industry tailwind. What narrows is the relative risk advantage that market leadership used to carry.

Credit moves in the same direction. Relative to the smallest competitor in the same highly exposed market, a market leader has about 3.8% less drawn credit and 2.4% less committed credit per standard deviation of attention. The quarterly probability that one of its lending relationships ends rises by 1.2 percentage points against a base of 7.1%, and its probability of adding a new lender falls by 0.6 percentage points against a base of 2.2%. Over the same period, higher-ranked firms in less exposed markets moved in the opposite direction on both margins. The same market-position pattern appears in subsequent repayment performance. In highly exposed markets, the advantage that higher-ranked firms have in avoiding arrears or payments more than 90 days overdue over the following year narrows by 0.5–0.7 percentage points per standard deviation of attention (base rate 8.2%), and this holds after conditioning on the average PD the firm’s lenders had already assigned.

Three caveats should be kept in mind. First, we document how banks revised their assessments, not that AI has in fact made exposed firms safer. The within-market reordering is mirrored in subsequent repayment performance, but this shows that the two patterns coincide; it does not by itself establish whether banks anticipated the deterioration or responded to early signs of it. The average industry markdown and the additional optimism of specialised lenders cannot yet be validated within the short window since ChatGPT's release; on our data, the disagreement between specialists and their co-lenders does not predict which side was right. Second, AI exposure is measured at the level of the borrower's industry, not from any observed adoption of the technology by the individual firm. Third, the credit results describe how lending moved alongside the reassessment; we do not separate lender decisions from borrower demand.

Three implications follow for central banks and supervisors. First, beliefs about technological change move through the financial system before the technology's productivity and competitive effects are observable. Because internal PDs feed pricing, limits and, for IRB banks, regulatory capital, a shift in how lenders read an industry can relax balance-sheet constraints on that industry ahead of any realised change in its fundamentals. Second, the shift is distributional and not merely a change in level: inside exposed markets, credit and lending relationships shift away from established leaders towards lower-ranked competitors, so the banking system is not only forming expectations about how competition will evolve but also influencing how it plays out. Third, the favourable reassessment is concentrated among the lenders whose portfolios are already most exposed to the affected sectors. Should that reading prove too optimistic, the resulting exposures would sit in the same institutions. How sectoral specialisation interacts with the re-rating of technologically exposed borrowers is therefore a reasonable object of supervisory attention, as is the erosion of the historical regularity that market leaders are the safer credits.

1 Introduction

The emergence of a new general-purpose technology creates large economic opportunities, but also makes the identity of winners and losers unusually difficult to determine in real time. Their eventual effects often depend on complementary investments in organizational capital, skills, and business processes, while their diffusion can simultaneously erode the value of existing assets and capabilities (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998; Brynjolfsson et al., 2019). Generative artificial intelligence is a particularly salient example. For firms in AI-exposed industries, the technology may automate costly tasks, raise worker productivity, improve decision-making, and enable new products and scalable business models. Yet the same exposure may also signal vulnerability: AI can displace existing capabilities, compress margins, and require costly organizational adjustment (Acemoglu and Restrepo, 2019; Brynjolfsson et al., 2025b; Firooz et al., 2026). Consistent with these competing channels, recent evidence documents both substantial productivity gains from generative AI and adverse effects on workers and activities that the technology can substitute (Noy and Zhang, 2023; Brynjolfsson et al., 2025b; Dell’Acqua et al., 2026; Hui et al., 2023). Exposure to AI therefore does not map mechanically into economic benefit.

A separate source of uncertainty concerns how these effects are distributed among firms competing within AI-exposed markets. Market leaders may be better positioned to respond to technological change because they control complementary assets (e.g., proprietary data, established customer relationships, distribution networks, organizational capital, and financial resources) that can be critical for appropriating the value of new technologies (Teece, 1986; Farboodi et al., 2019; Babina et al., 2024; Azoulay et al., 2025).¹

¹Consistent with the possibility that complementary assets matter, Babina et al. (2024) finds that the effects of AI investment on firm growth are stronger among larger firms.

At the same time, AI may weaken some of the advantages traditionally associated with established market position. By lowering the costs of experimentation, product development, and other knowledge-intensive activities, generative AI may reduce some of the resources required to develop and scale new business opportunities (Marchesi and Tang, 2025; Bena et al., 2026; Cai et al., 2025). It may also alter the value of existing technologies, workforces, and organizational routines, raising adjustment costs for firms with larger established operations and greater exposure to legacy production structures. Recent theory accordingly predicts that AI diffusion can either increase or reduce market concentration, depending on which firms adopt the technology and how widely it diffuses (Firooz et al., 2026). Whether generative AI ultimately reinforces or erodes the advantages associated with market leadership is therefore ambiguous *ex ante*.

To examine how these competing forces are assessed before their consequences become observable, we use banks as real-time interpreters of the rise of generative AI. Banks must form views about technological change before its effects are fully visible in firms' financial statements. They must continuously assess borrowers' future performance and creditworthiness, including for private firms for which public signals are generally unavailable. Their internal probability-of-default (PD) estimates therefore provide a particularly useful forward-looking measure of how sophisticated economic agents interpret an ambiguous technological shock. Recent evidence shows that such internal assessments contain genuine private information and predict subsequent outcomes beyond observable borrower and loan characteristics (Howes and Weitzner, 2025; Beyhaghi et al., 2025).

We use these assessments to trace both the average and distributional consequences banks associate with the AI shock. We find that banks reassess highly AI-exposed borrowers favorably on average, with weaker responses for labor-intensive firms and stronger responses among industry-expert lenders. At the same time, they systematically re-rank firms within AI-exposed markets, narrowing the relative risk advantage of market leaders. Credit allocation moves in the same direction, and the reordering predicts subsequent bad-credit

outcomes.

We conduct the analysis using AnaCredit, the harmonized credit register maintained by the European System of Central Banks. AnaCredit provides quarterly information on bank credit to legal entities, including each lender's internal estimate of a borrower's probability of default, the amount of drawn and committed credit, and the structure and evolution of the lending relationship. We study nonlisted, nonfinancial firms in Germany, France, Italy, and Spain between 2021Q1 and 2024Q4. We match borrowers to financial statements from Orbis and construct a firm–bank–quarter panel containing approximately 6.8 million observations in the baseline estimation sample.

A central feature of AnaCredit is its multi-lender structure. When a firm borrows from several banks, we observe the PD that each bank assigns to the same firm at the same point in time. We can therefore distinguish changes in a borrower's circumstances from differences in lenders' interpretations of those circumstances. The data also allow us to compare continuing lending relationships within the same bank and product market, and to examine whether changes in relative risk assessments are followed by changes in credit quantities, lender matching, and subsequent credit performance.

We measure AI exposure at the borrower-industry level using several complementary measures from the recent literature. Our baseline measure is the language-modeling variant of the AI Industry Exposure developed by [Felten et al. \(2023\)](#), building on the broader exposure framework of [Felten et al. \(2021\)](#). This measure links AI applications to the occupational abilities used in different jobs and aggregates occupational exposure to industries using employment shares; the language-modeling variant places greater weight on AI capabilities related to language understanding and generation, making it especially relevant for the generative-AI shock associated with ChatGPT. We also use the broad version of the same index, which captures exposure to AI technologies beyond language models. As alternatives, we use the large-language-model exposure measure of [Eloundou et al. \(2024\)](#), which assesses whether access to an LLM could substantially reduce the time required to

complete occupational tasks; the generative-AI exposure measure of [Eisfeldt et al. \(2026\)](#), which maps generative-AI capabilities to the task content of firms' workforces; and the AI-intensity taxonomy of [Calvino et al. \(2024\)](#), which classifies industries according to indicators of AI-related human capital, innovation, exposure, and use.

Our empirical analysis proceeds in three stages. We first estimate banks' average reassessment of AI-exposed borrowers and examine how it varies with lender information and borrower production structure. We then study whether banks re-rank competitors within the same product market as AI becomes salient. Finally, we examine whether this re-ranking is reflected in credit allocation and subsequent credit performance.

To estimate the average reassessment, we interact borrowers' industry-level AI exposure with country-quarter measures of public AI attention, constructed from Google search intensity for AI-related queries and views of AI-related Wikipedia pages.² Firm fixed effects absorb permanent differences across borrowers, while bank-by-country-by-quarter fixed effects absorb lender-specific changes in rating standards, risk appetite, and responses to macroeconomic conditions. A one-standard-deviation increase in either attention measure is associated with an approximately 5% decline in the PD of borrowers in the top quartile of AI exposure relative to other borrowers. These borrowers also move about one percentile toward the safer end of their banks' portfolios. The estimates are essentially unchanged when firm-bank fixed effects absorb all time-invariant characteristics of the lending relationship, so identification comes from changes in the same bank's assessment of the same borrower over time, and are directionally consistent across alternative measures of AI exposure.

The common signal does not move all lenders alike. Among banks assessing the same borrower in the same quarter, a one-standard-deviation increase in AI attention leads lenders

²Both AI-attention measures are low and relatively stable before late 2022 and increase sharply following the public release of ChatGPT.

with pre-existing industry expertise to assign PDs about 11–16% lower than those of non-expert co-lenders. Long-standing relationship lenders, on the contrary, assess the same AI-exposed borrowers no differently from their co-lenders, either in levels or in portfolio rankings. Borrower production structure also matters: assessed PD falls by roughly 7% for firms with below-median labor intensity but only 3% for labor-intensive firms.

We next examine whether the favorable industry-level reassessment changes the perceived hierarchy of firms within AI-exposed markets. We define product markets as country-by-NACE four-digit cells and measure firms' pre-ChatGPT market positions using their percentiles in the market's 2019–2021 sales distribution. Firm–bank fixed effects absorb all time-invariant borrower–lender heterogeneity, while bank-by-market-by-quarter fixed effects absorb contemporaneous market-wide shocks and each bank's overall assessment of that market. Identification therefore comes from changes in how the same bank assesses firms at different pre-shock market positions within the same market and quarter.

We find that a one-standard-deviation increase in AI attention is associated with roughly 8% higher assessed default risk for a market leader relative to a firm at the bottom of the pre-shock market-position distribution. The same pattern appears in banks' within-market PD rankings and strengthens monotonically with pre-shock market position.

The reordering is economically consequential. Relative to firms at the bottom of the pre-shock market-position distribution, market leaders experience approximately 3.9% less drawn credit and 2.4% less committed capacity as AI attention rises. Existing relationships are 1.2 percentage points more likely to terminate, while the probability of attracting a new lender falls by 0.6 percentage points. The same pattern appears in subsequent credit outcomes: as AI attention rises, the gap in the probability of experiencing a bad-credit event over the following four quarters between market leaders and lower-ranked firms narrows by 0.5–0.7 percentage points in highly AI-exposed markets, even conditional on banks' contemporaneous consensus PD. Banks' early interpretation of the AI shock therefore contains information about where subsequent credit deterioration occurs.

AI exposure is therefore favorable on average but accompanied by a pronounced reordering within affected markets. Banks lower PDs for highly exposed borrowers overall, yet within those same markets they narrow the relative safety advantage of firms that entered the shock with stronger market positions. Credit quantities and lender relationships shift in the same direction. Internal PDs thus provide a forward-looking, bank-implied measure of expected creative destruction among existing private firms: they reveal changes in relative competitive prospects, while showing that financing adjusts as those expectations form.

Our paper contributes to two strands of literature. First, we contribute to the rapidly growing literature on the economic consequences of artificial intelligence. Experimental and field evidence documents substantial productivity effects among writers, software developers, customer-support agents, and professional knowledge workers, with pronounced heterogeneity across workers and tasks (Noy and Zhang, 2023; Peng et al., 2023; Brynjolfsson et al., 2025b; Dell’Acqua et al., 2026). At the firm level, AI investment and exposure affect labor demand, employment, innovation, and firm growth (Alekseeva et al., 2021; Babina et al., 2024; Hui et al., 2023; Brynjolfsson et al., 2025a).

A related literature studies how AI may reshape firm dynamics, market structure, and competition. Control over complementary assets can allow established firms to appropriate a disproportionate share of the value created by new technologies (Farboodi et al., 2019; Azoulay et al., 2025), while emerging evidence on generative AI points to lower experimentation and entry costs and increased firm formation in more exposed industries (Marchesi and Tang, 2025; Bena et al., 2026; Cai et al., 2025). These opposing forces imply that AI diffusion need not have a uniform effect on existing market structure and may either strengthen or erode established market positions (Firooz et al., 2026).

Within finance, Eisfeldt et al. (2026) shows that firms with greater workforce exposure to generative AI earned higher equity returns following ChatGPT, while Jha et al. (2024) uses conference calls to measure managers’ anticipated ChatGPT-related investment responses. Becker and Ivashina (2023) shows that innovative disruption predicts subsequent incumbent

defaults and higher bond yields. For AI specifically, [Gandhi et al. \(2026\)](#) finds wider bond spreads for firms more exposed to generative AI, while [Yao et al. \(2026\)](#) links broader AI disclosure to higher bond spreads. In bank lending, [Liu et al. \(2024\)](#) finds higher loan rates and more contingent contracting for firms investing more heavily in AI, whereas [Haque et al. \(2026\)](#) shows that bank credit facilitates AI adoption and that adoption is followed by more credit at lower spreads. We contribute by using banks' forward-looking assessments to measure expected technological reordering among private firms and to trace how those expectations are reflected in credit.

Second, we contribute to the literature on banks as information producers. Classic theories emphasize banks' role in screening and monitoring opaque borrowers ([Diamond, 1984](#); [Fama, 1985](#)), while the relationship-lending literature studies information accumulated through repeated bilateral interactions ([Petersen and Rajan, 1994](#); [Berger and Udell, 1995](#); [Boot, 2000](#); [Bharath et al., 2011](#); [Liberti and Petersen, 2019](#)). Recent evidence shows that specialized lenders extend more favorable terms and achieve better ex post loan performance, consistent with superior information about the industries in which they specialize ([Blickle et al., 2025](#); [Simoens and Tamburrini, 2025](#)).

Our analysis also builds directly on recent work showing that banks' internal credit assessments contain information about borrowers' future performance beyond publicly observable characteristics ([Howes and Weitzner, 2025](#); [Beyhaghi et al., 2025](#)). We use these assessments to study a different dimension of bank information production: how lenders interpret a common, newly salient, and economically ambiguous technological shock. This relates to evidence that bank information facilitates firms' innovation and technology adoption ([Herrera and Minetti, 2007](#)) and that the cost of acquiring information about newly relevant borrower characteristics affects credit allocation, as in the greening of bank loan portfolios ([Buchetti et al., 2024](#)). We extend this literature from the evaluation of existing borrower quality to the interpretation of a new technological shock.

2 Data and Sample Construction

For our analysis, we combine AnaCredit, which provides quarterly bank–firm credit exposures and lender-specific internal probability of default (PD) estimates, with Orbis firm financial data, industry-level measures of AI exposure, and country–quarter measures of public attention to AI. We use these sources to construct a firm–bank–quarter panel of nonlisted, nonfinancial firms in Germany, France, Italy, and Spain over 2021Q1–2024Q4.

AnaCredit. Our primary data source is *AnaCredit* (Analytical Credit Datasets), the harmonized euro-area credit register maintained by the European System of Central Banks. AnaCredit records, at monthly frequency (aggregated to quarterly frequency for our sample), the universe of credit exposures of euro-area banks to legal entities above a €25,000 reporting threshold, together with detailed instrument-, counterparty-, and protection-level attributes. Most important for our analytical purposes, it reports each lending bank’s internal estimate of the borrower’s *probability of default* (PD), the forward-looking risk assessment that feeds the bank’s credit decisions and, for banks on the internal ratings-based (IRB) approach, its risk-weighted assets. The reported PD is the bank’s estimate of the probability that the counterparty defaults over a one-year horizon, produced by the lender’s own credit-risk models. It is a decision-relevant object rather than a statistical byproduct: internal PDs typically feed loan origination and monitoring, provisioning, internal limit systems, and loan pricing, in addition to regulatory capital for IRB banks. Banks act on these numbers and they move credit (Buchetti et al., 2026).

Internal assessments of this kind have been shown to embody genuine private information: in analogous U.S. supervisory data, banks’ confidential risk ratings predict loan outcomes beyond observable firm characteristics and public market signals (Beyhaghi et al., 2025; Howes and Weitzner, 2025). Because each lender produces its own estimate, the same borrower can carry different PDs at different banks in the same quarter. We also observe the outstanding

and undrawn amounts of each exposure and the interest rate charged.

Because a borrower typically obtains credit from several banks, AnaCredit allows the assembly of a *firm–bank–quarter* panel in which, for a given firm in a given quarter, we observe the PD assigned by each of its lenders. We focus on the four largest euro-area economies (Germany, France, Italy, and Spain) over 2021Q1–2024Q4, and restrict attention to non-financial corporate borrowers. In addition to PD levels, we measure borrowers’ relative risk using *portfolio PD rank*, defined as the percentile rank of $\ln(\text{PD})$ within a bank’s country portfolio in each quarter. We compute the rank only for bank $\times$ country $\times$ quarter cells with at least 20 borrowers.

Orbis firm financials. We obtain borrower financial statements from *Orbis* (provided by Bureau van Dijk, a Moody’s Analytics company), which compiles standardized balance-sheet and P&L data from national business registries. Orbis is well suited to our setting because, unlike databases restricted to publicly listed firms, it provides broad coverage of *private* firms in the four sample countries, where the filing of annual accounts is mandatory. The bank-dependent borrowers that populate AnaCredit are precisely the firms for which such coverage is essential and for which market-based information is unavailable. We link AnaCredit counterparties to Orbis through the Bureau van Dijk identifier (BvD ID), which serves as our firm identifier throughout; the large majority of corporate borrowers in the four countries are successfully matched to an Orbis record.

From each firm’s annual accounts we draw total assets, operating income (EBIT), cash holdings, long-term debt, the number of employees, the listed-firm indicator, and the date of incorporation. Because financial statements are reported annually whereas credit data are quarterly, we match each firm–bank–quarter observation to the firm’s most recently available fiscal-year accounts; given the lag with which statements are filed and digitized, these accounts are predetermined relative to the quarter’s credit outcomes, so the resulting controls are not contaminated by contemporaneous shocks.

From these items we construct the firm-level controls used throughout the paper: the logarithm of total assets, the logarithm of (one plus) employment, EBIT, cash, and long-term debt each scaled by total assets, and firm age, defined as the difference between the observation year and the year of incorporation. All ratio and log controls are winsorized at the 1st and 99th percentiles.

Within-market portfolio PD rank. Based on the NACE4 code reported on Orbis, we define a *market* as a country–NACE 4-digit industry cell containing at least 20 firms with positive sales in the Orbis universe. The 4-digit level is the narrowest industry classification available for the full universe of private firms and comes closest to a set of direct product-market competitors. Table A.3 reports the distribution of cell sizes by country, the bite of the 20-firm floor, and the NACE 3-digit alternative used in robustness. Within each market, a firm’s *incumbency rank* is its percentile in the distribution of mean fiscal 2019–2021 sales among these firms, from 0 for the smallest to 1 for the market leader. The rank is computed on pre-ChatGPT accounts and held fixed throughout, so it measures a firm’s product-market standing right before the AI shock.

The *within-market PD rank* carries the bank’s assessment to the same level: it is the firm’s percentile of $\ln(PD)$ among borrowers of the same bank in the same market and quarter (cells with at least 5 borrowers). While the portfolio PD rank locates a borrower in the bank’s overall book, the within-market rank locates it among its direct product-market peers, as assessed by the same lender at the same moment. The ranks are zero-sum within a cell. A shock that moves every firm in a market by the same amount, including any average reassessment of the market’s AI exposure, leaves each firm’s within-market rank unchanged, so the outcome responds only when the bank reorders firms inside the market. An average, market-wide reassessment appears in $\ln(PD)$ and in the portfolio rank, but cannot, by construction, appear in the within-market rank.

AI exposure measures. We characterize borrowers' exposure to artificial intelligence at the level of their industry (NACE 2-digit), using five measures drawn from the recent literature. The first four share a common logic: they map AI capabilities onto the task or ability content of occupations and aggregate occupational exposure using employment composition. The fifth instead captures realized industry-level AI intensity. They differ, however, in terms of which AI capabilities they emphasize, the data used to assess exposure, and their granularity.

Our baseline measure is the language-modeling variant of the AI Industry Exposure index (AIIE-LM) of Felten et al. (2023), which builds on the broader AI exposure measure of Felten et al. (2021). The index is built in two steps. First, occupational exposure links a set of AI application areas (e.g., image recognition, language modeling, translation, and abstract strategy games) to the 52 workplace abilities catalogued in O*NET (the Occupational Information Network), using crowd-sourced assessments of how relevant each application is to each ability; an occupation's exposure aggregates these links according to the prevalence and importance of its abilities.³ Second, occupational exposure is aggregated to industries using occupational employment shares.

The language-modeling variant up-weights the language-modeling application, capabilities related to language understanding and generation, aligning the measure with the generative-AI technologies that ChatGPT brought to prominence. We also use the broad variant (*AIIE-BR*), which weights all application areas equally and therefore captures exposure to AI in general rather than to language models in particular. We map each index to the European industry classification (NACE Rev. 2, two-digit divisions), the level at which borrowers'

³O*NET (the Occupational Information Network) is the primary source of occupational information in the United States. Sponsored by the U.S. Department of Labor, it is a free online database that profiles over 900 occupations across the U.S. economy.

industries are recorded in AnaCredit.

The remaining three measures provide alternative ways of capturing AI exposure. [Eloundou et al. \(2024\)](#) construct a task-based measure of exposure to large language models (LLMs). Human annotators and GPT-4 classify O*NET tasks according to whether access to an LLM alone, or to additional software built on top of an LLM, could reduce completion time by at least half while maintaining output quality. These task-level assessments are then aggregated to occupations. Thus, like AIIE-LM, the measure is designed to capture exposure to language-model technologies, but it assesses exposure directly from occupational tasks rather than indirectly through the abilities required by an occupation.

[Eisfeldt et al. \(2026\)](#) construct a closely related task-based measure of generative-AI exposure. They use an LLM to score O*NET tasks according to whether generative-AI tools can substantially increase task productivity, distinguishing between direct exposure and exposure that requires complementary software, and aggregate these scores to occupations. Their original measure then combines occupational exposure with firm-specific occupational employment shares and separately considers exposure through core and supplemental tasks. For our industry-level analysis, we aggregate their occupation-level exposure measure to NACE 2-digit industries using occupational employment shares and label the resulting measure *ESTZ*.

Finally, [Calvino et al. \(2024\)](#) take a different approach and measure AI intensity directly at the industry level. Their taxonomy combines four indicators: the prevalence of AI-related job vacancies, AI-related patenting, exposure to AI adjusted for barriers to adoption, and the share of firms using AI. Industries are then classified into High, Medium, and Low AI-intensity groups. Unlike the occupation-based measures above, the Calvino taxonomy therefore combines potential exposure with indicators of AI investment, innovation, and actual use.

Two distinctions organize these measures. First, AIIE-LM, Eloundou, and ESTZ are oriented toward language-model or generative AI, whereas AIIE-BR captures a broader set

of AI capabilities. Second, the four occupation-based measures quantify potential exposure based on the work performed in an industry, whereas Calvino combines potential exposure with observed indicators of AI-related human capital, innovation, and use. We adopt AIIE-LM as our baseline because it is continuous, language-model weighted, and widely used, and report the remaining measures as alternatives.

For each continuous measure, we define a *high-AI-exposure* indicator equal to one when a borrower’s industry score lies in the top quartile of the observation-weighted distribution in the estimation sample. We compute the cutoff once using the full filtered panel and hold it fixed throughout the analysis. Thus, the indicator identifies industries associated with the top quartile of credit-exposure observations, rather than the top quartile of industry codes. For the Calvino taxonomy, we instead classify industries in the High tier as high AI exposure.

AI attention. We measure public attention to AI in each country and quarter using two indices. The first is based on Wikipedia: for each country we aggregate quarterly pageviews of the country-language articles for “Artificial intelligence” and “ChatGPT” (for example, the German-language pages for Germany). The second is based on Google Trends: for each country we aggregate, within the quarter, search intensity for the queries “AI” and “ChatGPT.” Using country-language pages and country-level search behavior allows the indices to capture attention among each country’s public rather than global English-language interest.

We take the natural logarithm of one plus each raw series and standardize it to zero mean and unit standard deviation across the pooled country–quarter panel, so that regression coefficients are interpreted per standard deviation of attention. Figure 1 plots the two indices, averaged across the four countries: both are low and stable through 2022Q3, jump in 2022Q4 when ChatGPT was released to the public, and remain persistently elevated (roughly two standard deviations above their pre-release level) through the end of 2024. The two indices co-move closely, and we report all attention-based results using both.

Sample construction. We build the estimation sample from the firm–bank–quarter panel as follows. First, we restrict the sample period to 2021Q1–2024Q4. This window includes seven quarters of pre-ChatGPT data while avoiding the most acute phase of the pandemic. Second, we exclude financial and public-sector borrowers (NACE 2-digit divisions 64–66 and 84). Third, we drop listed firms to focus on the bank-dependent firms for which AnaCredit PDs are most informative. Fourth, we require non-missing current and lagged PD, positive total assets, and non-missing AI-exposure measures. Fifth, we drop firm–quarters in which any lender reports a current or one-quarter-lagged PD of 0.9 or above to remove the mechanical influence of default on assessed risk. Sixth, because a small share of firms are recorded under more than one NACE 2-digit code across the panel, we assign each firm its *modal* industry and hold it fixed. The resulting sample comprises roughly 6.8 million firm–bank–quarter observations.

Industry distribution and summary statistics. Table A.1 lists the five most and five least AI-exposed industries under each measure. The rankings are intuitive and broadly consistent across measures: the most exposed industries are knowledge- and information-intensive services (i.e., legal and accounting, computer programming and consultancy, information services, publishing, and scientific R&D), while the least exposed are primary and manual industries such as agriculture, forestry, specialized construction, and the manufacture of wood, leather, and paper. The overlap across measures is high: computer programming, information services, and legal and accounting appear near the top of nearly every measure. Moreover, the AI-intensity tiers of [Calvino et al. \(2024\)](#) align with the continuous scores, in that the most exposed industries are uniformly classified as “High” intensity.

Table 1 reports summary statistics for our main variables. The assigned PD averages 2.7% with a median of 0.8%, reflecting the right-skewed distribution of credit risk, and loan rates average roughly 3–3.6%. The median borrower maintains a lending relationship of three years and borrows from a single bank in many cases (the mean lender share is 0.58),

underscoring the bank-dependence of the sample. Firms are mature on average (median age 18 years), and the firm-level controls exhibit the usual cross-sectional dispersion in size, profitability, and leverage.

3 Average Reassessment of AI-Exposed Borrowers

We begin by estimating how banks reassessed AI-exposed borrowers on average as AI became salient. Specifically, for firm i borrowing from bank b in country c during quarter t , we estimate

$$\ln PD_{ibt} = \beta (HighAI_i \times Attention_{ct}) + \Gamma'_R R_{ib,t-1} + \Gamma'_F F_{i,FY(t)-1} + \alpha_i + \alpha_{bct} + \varepsilon_{ibt}, \quad (1)$$

where $\ln PD_{ibt}$ is the log of the PD that bank b assigns to firm i in quarter t .⁴ We use the log of the PD because assessed default risk is strongly right-skewed (Table 1); coefficients are therefore interpreted as proportional effects on assessed risk. $Attention_{ct}$ is the standardized AI-attention index in the firm's country. $HighAI_i$ equals one if the AIIE-LM score of firm i 's industry, which is classified by its modal NACE 2-digit code over the sample period, lies strictly above the 75th percentile of the score's observation-level distribution in the estimation panel. The cutoff is computed once on the full filtered panel and held fixed across all specifications.

Firm fixed effects α_i absorb all time-invariant differences across borrowers, including their industry and hence their unconditional AI exposure. Bank-by-country-by-quarter fixed effects α_{bct} absorb changes in each lender's overall rating standards, balance-sheet condition,

⁴Reported PDs are bounded to $(10^{-6}, 1 - 10^{-6})$ before taking logs. The lower bound binds only for the 1.4% of observations with a reported PD of exactly zero, which enter as $\ln(10^{-6})$ rather than dropping out of the sample; the upper bound never binds after the high-PD filter.

and response to country-level macroeconomic developments, including the level of AI attention itself. Identification of our coefficient of interest β therefore comes from whether a given bank differentially changes its assessment of more AI-exposed borrowers as AI becomes more salient, relative to its contemporaneous assessments of its other borrowers in the same country.

The controls enter as two blocks. The relationship controls $R_{ib,t-1}$ capture the size and structure of the bank–firm exposure at the end of the previous quarter: the log committed exposure, the undrawn share of the commitment, and the bank’s share of the firm’s total credit, together with the log length of the lending relationship. The fundamentals $F_{i,FY(t)-1}$ are taken from the borrower’s previous-fiscal-year accounts: the logarithms of total assets and of employment, and profitability, cash holdings, and leverage each scaled by total assets; together with firm age. All controls are thus predetermined relative to the quarter- t assessment. Standard errors are double-clustered by firm and by bank for all analyses.

3.1 Baseline estimates

Table 2 reports the estimates. In column (1), the interaction of the high-AI-exposure indicator with Google AI attention has a significant coefficient of -0.054 . Economically, this implies that a one-standard-deviation increase in AI attention is associated with an approximately 5% decline in the assessed PD of borrowers in the top quartile of AI exposure relative to other borrowers. The Wikipedia index delivers a nearly identical estimate (column (2)). Relative to the sample median PD of 0.8%, a 5% relative decline corresponds to roughly four basis points of assessed default risk per standard deviation of attention, while it is roughly fourteen basis points relative to the mean PD of 2.7%.

Columns (5) to (6) apply the same design to the portfolio PD rank. The interaction is -0.011 ($t = -3.56$) under Google attention and -0.010 ($t = -4.09$) under Wikipedia attention, suggesting that as AI attention rises by one standard deviation, an AI-exposed

borrower moves roughly one percentile toward the safe end of its bank’s country-level book. The reassessment therefore shifts not only the level of assessed risk but the borrower’s position in the lender’s overall portfolio ordering. Banks re-file AI-exposed borrowers among their safer credits. Estimates with the standardized continuous exposure score in place of the top-quartile indicator are reported in Appendix Table A.4: a one-standard-deviation increase in exposure is associated with a 0.7–0.9% relative PD decline per standard deviation of attention, while the rank response is small and at most marginally significant. The much larger effect of the top-quartile indicator than of the continuous score implies a convex dose–response: the reassessment is concentrated in the most exposed industries.

Taken together, the estimates indicate a relative improvement in the perceived credit-worthiness of AI-exposed borrowers as AI became salient. Banks, on average, seem to read AI exposure as a credit tailwind rather than a credit headwind.

Within-relationship estimates. The firm fixed effects in equation (1) leave one composition margin open: if highly AI-exposed borrowers shifted their borrowing toward banks that assign systematically lower PDs as AI attention rose, part of the estimated markdown could reflect the re-matching of firms and banks rather than revised assessments. Columns (3) to (4) and (7) to (8) of Table 2 therefore replace the firm fixed effects with firm×bank pair fixed effects, which nest them and additionally absorb any time-invariant component of assessed risk specific to a bank–firm match. Identification then comes exclusively from changes in the PD that a given bank assigns to a given borrower within a continuing lending relationship, and the median relationship is observed for nine quarters.

The estimates are essentially unchanged: -0.052 ($t = -2.25$) and -0.050 ($t = -2.15$) for the top-quartile indicator with the Google and Wikipedia indices on $\ln(PD)$, -0.010 throughout for the portfolio rank, and -0.007 and -0.009 per standard deviation of the continuous score (Appendix Table A.4), even though the pair effects raise the explanatory power of the model substantially (R^2 rises from 0.61 to 0.74). The favorable reassessment

of AI-exposed borrowers is thus a re-rating of existing exposures, not a recomposition of lending relationships.

Alternative measures of AI exposure. The results do not hinge on a particular measure of AI exposure. Table 3 re-estimates the within-relationship specification using the four alternative measures described in Section 2, for both outcomes.⁵

On $\ln(PD)$, the interaction of top-quartile exposure with AI attention is negative and statistically significant for the task-level LLM exposure of Eloundou et al. (2024) (-0.035 and -0.032 for the Google and Wikipedia indices), for the AI-intensity taxonomy of Calvino et al. (2024) (-0.023 and -0.021), for the generative-AI skill exposure of Eisfeldt et al. (2026) (-0.034 and -0.031), and for the broad variant of the Felten–Raj–Seamans index (-0.052 and -0.051 as an indicator; -0.008 and -0.009 continuously).

The portfolio-rank estimates mirror this pattern measure for measure, so the portfolio-wide rank shifting is not specific to the language-modeling weighting either.

3.2 Lender industry expertise and relationship lending

Having established that banks lower assessed risk for AI-exposed borrowers on average, we next exploit the multi-lender structure of the data to examine whether lenders differ in their assessments. As AI attention rises, the dispersion of PDs assigned by different banks to the same AI-exposed borrower increases across all measures of disagreement (Appendix Table A.5). The average reassessment therefore masks meaningful heterogeneity across lenders.

We ask whether this heterogeneity is related to lender information. Both sectoral expertise and relationship-specific familiarity may shape how banks interpret AI exposure: the

⁵Because the exposure measures differ in industry coverage, the estimation sample varies across measures.

former captures knowledge of industry business models and competitive conditions, while the latter captures private information accumulated through repeated lending to the borrower. We test these channels by comparing banks that lend to the same firm in the same quarter.

We examine the influence of these two sources of lender information as follows. Our measure for *sectoral expertise* is based on a bank's portfolio composition: a bank is classified as an industry expert for a given borrower when more than 10% of its pre-ChatGPT (2022Q3) corporate portfolio is concentrated in the borrower's NACE 2-digit industry.⁶ Using a pre-determined portfolio share limits the possibility that the expertise measure itself responds to the subsequent AI shock.

The second measure proxies for *relationship-specific* information, accumulated through repeated bilateral interaction. Specifically, we classify a bank as a relationship lender when, in 2022Q3, it had lent to the borrower for more than three years (the sample median relationship length). As with the expertise measure, the indicator is fixed at its pre-ChatGPT value so that it cannot respond to the subsequent shock. As a result, the relationship specifications are estimated on bank–firm pairs that existed in 2022Q3.

To compare the assessments that differently informed banks make of the same borrower, we estimate, on the subsample of firms with multiple lenders,

$$\ln PD_{ibt} = \beta (HighAI_i \times Attention_{ct} \times Expert_{ib}) + \delta' W_{ibt} + \Gamma'_R R_{ib,t-1} + \alpha_{it} + \alpha_{bct} + \varepsilon_{ibt}, \quad (2)$$

where W_{ibt} represents the set of lower-order terms that are not absorbed by the fixed effects.

⁶The fixed portfolio-weight cutoff follows the logic of Fich et al. (2015), which classifies an institutional investor as a motivated monitor of the stocks that carry a large weight in its portfolio: positions that account for a meaningful share of the portfolio warrant attention and information acquisition. Replacing the indicator with the continuous (log) portfolio share yields the same conclusion, with the AI-specific reassessment deepening significantly in the intensity of specialization.

The key change relative to equation (1) is the inclusion of firm-by-quarter fixed effects α_{it} . These absorb every observed and unobserved borrower characteristic that is common across its lenders in a given quarter (e.g., the firm’s financial condition, investment decisions, realized AI adoption, and exposure to contemporaneous demand or supply shocks).

The estimates are therefore identified exclusively by differences among banks evaluating the same borrower in the same quarter. Bank-by-country-by-quarter fixed effects continue to absorb lender-wide changes in ratings and risk appetite, and X_{ibt} continues to condition on the structure of the bank–firm exposure.

Results. Table 4 reports the estimates. Industry-expert banks become substantially more optimistic about AI-exposed borrowers as AI attention rises. In column (1), the triple interaction of high AI exposure, Google attention, and the industry expert indicator has a significant coefficient of -0.117 ; with the Wikipedia index (column (4)) it is -0.173 ($t = -3.56$). For a one-standard-deviation increase in AI attention, the expert–nonexpert PD ratio declines by approximately 11–16% for highly AI-exposed borrowers relative to the corresponding change for other borrowers.

Relationship lenders show no comparable pattern (columns (2) and (5)). The triple interaction is small, positive, and insignificant (0.004 and 0.009), even though relationship lenders assign lower PDs in general (the relationship main effect is -0.026). When expertise and relationship status jointly enter the regression (columns (3) and (6)), the expert effect is unchanged and the relationship effect remains zero.

Panel B repeats the design with the portfolio PD rank as the outcome, asking whether informed lenders not only assign lower levels but re-order their own books. We find that expert lenders do so. The triple interaction has a significant coefficient of -0.026 under Google attention and -0.040 under Wikipedia attention, two and a half to nearly four times the average rank reassessment of Table 2. The estimate is conservative, because a specialist’s portfolio by construction overweights the borrower’s industry, so an industry-wide

reassessment partly cancels within its own ranking. Relationship lenders neither reassess nor re-rank AI-exposed borrowers (-0.001 , $t \approx -0.5$).

Figure 2 traces when the lender-information differences arise. For high-AI borrowers, Panel A shows no pre-ChatGPT difference between expert and nonexpert lenders. The expert differential opens only after AI attention rises, with expert lenders assigning PDs roughly 16–27% lower than nonexpert co-lenders in late 2023 and 2024. Panel B shows no such pattern for relationship lenders, as the differential is never distinguishable from zero, before or after ChatGPT. The principal informational distinction therefore seems to be sectoral rather than bilateral: familiarity with the borrower alone does not account for the assessments made by banks with substantial experience in its industry.

Two additional results support an industry-expertise interpretation. First, the two-way interaction of the expert indicator with attention is *positive* (0.052 to 0.058, significant in all columns): outside highly AI-exposed industries, expert lenders became, if anything, relatively more conservative as AI attention rose. Their more favorable reassessment is therefore specific to AI-exposed borrowers rather than reflecting generally greater leniency among specialized lenders.

Second, the result is not driven by the 10% expertise threshold. Appendix Table A.6 replaces the indicator with the continuous (log) pre-ChatGPT portfolio share and reports the specification for both attention indices. The AI-specific reassessment becomes more favorable with greater specialization: a one-standard-deviation increase in log portfolio share is associated with an additional 6.6% reduction in PD under Google attention ($t = -2.86$) and a 10.3% reduction under Wikipedia attention ($t = -4.05$). The specialization result is robust across both attention indices, whereas the effect for pre-ChatGPT relationship length is small and at most marginal, consistent with the indicator estimates in Table 4. For the portfolio-rank estimates, greater industry specialization is also associated with a stronger favorable re-ranking of AI-exposed borrowers within the lender’s portfolio, whereas relationship length has little effect on their relative position.

3.3 Borrower production structure

We next examine whether the PD markdown for AI-exposed borrowers depends on firms' production structure. Specifically, whether AI exposure is a credit tailwind or headwind should depend on firms' reliance on labor.

For a borrower with relatively low labor intensity, AI may primarily enhance existing production processes, allowing efficiency gains to accrue with comparatively limited workforce disruption. For a labor-intensive borrower, whose production depends more heavily on its workforce, the same technology is more double-edged. Such firms may benefit more if AI reduces labor costs, but they may also face greater disruption risk and adjustment frictions if realizing these gains requires reorganizing production, retraining workers, or competing with faster adopters.

We measure a borrower's pre-ChatGPT labor intensity as its mean employees per unit of operating revenue over the quarters through 2022Q2. We interact this measure with the baseline reassessment, the interaction of high AI exposure with AI attention, and report it two ways: as an above-median indicator and as a standardized continuous measure.

Table 5 reports the estimates, showing that the favorable reassessment is significantly weaker for labor-intensive borrowers. As AI attention rises by one standard deviation, the assessed PD of a low-labor-intensity borrower falls by roughly 7%, whereas for a labor-intensive borrower the decline is only about 3%. The triple interaction is positive and significant at the 1% level across both the median-split and continuous specifications and under both attention indices. The same tempering appears in the portfolio PD rank (columns (5) to (8)): labor-intensive AI-exposed borrowers shift roughly half as far toward the safe end of the bank's book as their labor-light counterparts. All estimates in the table are identified within continuing lending relationships, with firm-bank pair fixed effects; the firm-fixed-effects counterpart in Appendix Table A.7 is essentially identical.

These results suggest that banks do not treat AI exposure as an unconditional tailwind.

They extend the favorable reassessment most strongly to borrowers whose production is less labor intensive, for whom AI is more plausibly an efficiency-enhancing technology, and temper it when labor is central to the firm’s business model and AI may instead be disruptive.⁷

4 Within-Market Re-Ranking of Competitors

The analysis so far has focused on how AI changes banks’ assessment of industries on average. Yet the consequences of AI need not be shared equally among firms competing in the same market. By changing the sources of competitive advantage, AI may alter which firms banks expect to gain or lose. We therefore turn from industry-level reassessment to within-market re-ranking and ask whether rising AI attention changes the relative assessed risk of competitors.

We define a market as a country–NACE 4-digit cell containing at least 20 firms with positive sales in the Orbis universe. Within each market, the *incumbency rank* captures a firm’s position in the pre-ChatGPT sales distribution, ranging from 0 for the smallest firm to 1 for the market leader. The *within-market PD rank* captures the firm’s assessed risk relative to other borrowers of the same bank in the same market and quarter.

For firm i in market m , borrowing from bank b during quarter t , we estimate

$$\begin{aligned} y_{ibt} = & \gamma (Rank_i \times HighAI_i \times Attention_{ct}) + \delta (Rank_i \times Attention_{ct}) + \Gamma'_R R_{ib,t-1} + \Gamma'_F \tilde{F}_{i,FY(t)-1} \\ & + \alpha_{ib} + \alpha_{bmt} + \varepsilon_{ibt}, \end{aligned} \tag{3}$$

⁷A salient example is the market reaction to Klarna’s February 2024 announcement that its AI customer-service assistant was performing work equivalent to roughly 700 full-time agents. Shares of Teleperformance, a major provider of outsourced customer services, fell as much as 29% that day amid concerns about AI-driven disruption to the call-center business.

where y_{ibt} is $\ln(PD)$ or the within-market PD rank. Firm–bank pair fixed effects α_{ib} again absorb time-invariant relationship heterogeneity, while bank×market×quarter fixed effects α_{bmt} absorb each bank’s market-wide reassessment in a given quarter, including the average industry-level reassessment captured by the *High AI* × *AI attention* interaction. Identification therefore comes from differences in how the same bank reassesses firms at different pre-shock market positions within the same market and quarter.

4.1 Results

Table 6 reports the estimates. In Panel A, where the dependent variable is $\ln(PD)$, the coefficient on *incumbency rank* × *High AI* × *AI attention* is 0.074 using Google attention and 0.075 using Wikipedia attention. Because the incumbency rank ranges from zero for the smallest firm to one for the market leader, a one-standard-deviation increase in AI attention implies that the market leader’s assessed PD rises by roughly 8% relative to that of the smallest firm in highly AI-exposed markets, compared with other markets. The *incumbency rank* × *AI attention* interaction is small and insignificant, indicating no comparable re-ranking outside highly AI-exposed markets. The magnitude of this within-market re-ranking is comparable to the average industry-level decline in assessed risk, but operates in the opposite direction for firms at the top of the market hierarchy.

The result is robust to defining markets at the NACE 3-digit level (columns (3)–(4)). It is also robust to adding size-decile×country×quarter or pre-ChatGPT PD-decile×country×quarter fixed effects (columns (5)–(8)), which restrict comparisons to firms of similar size or initial credit risk within the same country and quarter. Across these specifications, the triple-interaction coefficients range from 0.059 to 0.082 and remain statistically significant.

Panel B applies the same design to the *within-market PD rank*. The coefficient on *incumbency rank* × *High AI* × *AI attention* ranges from 0.011 to 0.014 across specifications. Thus, as AI attention rises by one standard deviation, the market leader moves roughly one

percentile point toward higher assessed risk relative to the smallest competitor in highly AI-exposed markets, compared with other markets. Because the distribution of within-market PD ranks is fixed within each bank×market×quarter cell, this movement reflects reordering among competitors rather than a market-wide change in assessed risk.

Dynamic effect of AI salience on re-ranking. Figure 3 traces the re-ranking in event time, plotting quarterly coefficients on Incumbency rank × High AI relative to 2022Q3. Before the release of ChatGPT the coefficients are individually indistinguishable from zero, with a mild *downward* drift — the opposite direction to the post-release pattern, so a continuation of the pre-path cannot generate the result.

From 2022Q4 the coefficient turns positive and strengthens, reaching 0.250 ($t = 4.81$) in 2024Q1, and eight of the nine post-release quarters are individually significant.

Figure 4 shows how the effect varies across the market hierarchy. We replace the linear incumbency rank in equation (3) with deciles of firms’ pre-ChatGPT market position. The estimated effect of AI attention increases steadily with market position: it is small and statistically insignificant for firms in the lower deciles, but becomes progressively larger toward the top of the market. For firms in the top decile, a one-standard-deviation increase in AI attention is associated with roughly a 10% increase in assessed PD in highly AI-exposed markets. Thus, the relative increase in assessed risk becomes larger with pre-ChatGPT market position rather than peaking among mid-ranked firms.

Robustness of re-ranking results. Appendix Table A.8 shows that the within-market re-ranking is robust to alternative measures of AI exposure, alternative constructions of firms’ pre-ChatGPT market position, and more stringent fixed effects specifications. In the most saturated specification, which simultaneously controls for six sets of pre-shock decile×country×quarter fixed effects, the coefficient on *incumbency rank* × *High AI* × *AI attention* is 0.076–0.078, implying a leader–smallest-firm differential in assessed PD of about

8%. Defining incumbency using sales in 2019 alone produces essentially the same estimate. By contrast, replacing sales rank with employment rank yields a positive but statistically insignificant coefficient. This distinction suggests that the result is tied to firms' position in the product market rather than to firm size more generally.

Appendix Table A.9 shows that this relative deterioration does not imply that market leaders become riskier in absolute terms. Firms in the top half of the pre-ChatGPT market-position distribution still experience a decline in assessed risk as AI attention rises. The within-market result therefore reflects a change in firms' risk *relative to their competitors*: market leaders benefit less than lower-ranked firms, rather than becoming riskier in absolute terms.

4.2 Credit Reallocation

Next, we examine whether the within-market re-ranking is also reflected in credit allocation by estimating the same *incumbency rank* $\times$ *High AI* $\times$ *AI attention* interaction for credit-quantity and lender-matching outcomes.

Table 7 reports the estimates, and Figure 5 summarizes them. Under Google attention, a one-standard-deviation increase in AI attention reduces the ratio of market leaders' drawn credit to that of the smallest firms by approximately 3.8% in highly AI-exposed markets relative to the corresponding change in other markets. The corresponding relative reductions are 1.2% in the number of lenders and 2.6% in drawn credit per relationship. Committed credit shows a relative reduction of 2.4% (Panel B, columns (5)–(6)).

Panel B reports changes in lending relationships. Under Google attention, a one-standard-deviation increase in AI attention raises the leader–smallest-firm difference in the probability that an existing relationship ends by an additional 1.2 percentage points in highly AI-exposed markets relative to other markets. The corresponding difference in the probability of adding a new lender falls by 0.6 percentage points. The sample-average exit and entry rates are

7.1% and 2.2%, respectively.

Jointly, this evidence suggests that the within-market re-ranking in assessed risk is accompanied by less credit and weaker lender relationships for market leaders relative to lower-ranked competitors.

4.3 Subsequent Credit Performance

We next ask whether the same market-position pattern appears in subsequent repayment performance. For each firm–quarter, we define a *bad-credit event* equal to one if, in any of the following four quarters, any lender reports arrears of at least 1% of outstanding exposure or at least 90 days past due. The outcome has a sample mean of 8.2%. We regress this indicator on $incumbency\ rank \times High\ AI \times AI\ attention$, with firm and market $\times$ quarter fixed effects and firm-level controls. The baseline specification also controls for the contemporaneous consensus $\ln(PD)$ across the firm’s lenders. Thus, the exercise asks whether the same market-position interaction that characterizes the PD re-ranking is also present in subsequent credit performance.

Table 8 reports the estimates. The coefficient on $incumbency\ rank \times High\ AI \times AI\ attention$ is 0.007 under Google attention and 0.005 under Wikipedia attention (columns (2) and (6)). Hence, for a one-standard-deviation increase in AI attention, the leader–smallest-firm difference in the probability of a bad-credit event over the following four quarters increases by an additional 0.5–0.7 percentage points in highly AI-exposed markets relative to other markets.

The estimates are unchanged when consensus PD is omitted (columns (1) and (5)) and remain positive when profitability is added to the control set (columns (3) and (7)). The same pattern is already visible at the one-quarter horizon: the corresponding coefficients are 0.005 under Google attention and 0.004 under Wikipedia attention (columns (4) and (8)), against a one-quarter bad-credit rate of 3.0%. Overall, the market-position pattern in

banks' risk assessments is mirrored in subsequent repayment performance: as AI attention rises, the relative advantage of higher-ranked firms in avoiding bad-credit events narrows in highly AI-exposed markets.

5 Conclusion

General-purpose technologies can change both the prospects of entire industries and the relative position of firms within them, yet these effects are difficult to assess while the technology is still emerging. This paper studies how banks interpreted the rapid rise of generative AI after the release of ChatGPT. Using AnaCredit data for firms in Germany, France, Italy, and Spain, we examine how lenders revised their assessments of borrower default risk as public attention to AI increased.

Banks viewed AI exposure favorably on average. As AI attention rose, lenders reduced the assessed default risk of borrowers in highly AI-exposed industries relative to other borrowers. The result is robust across alternative measures of AI exposure and is present within continuing bank–firm relationships, so it does not reflect changes in the composition of borrowers or lenders. The reassessment is nevertheless heterogeneous across firms. It is weaker for labor-intensive borrowers, consistent with greater uncertainty about the benefits of AI when labor is central to production.

Lenders also differ in how they assess the same AI-exposed borrower. Banks with greater pre-ChatGPT experience in the borrower's industry make a substantially more favorable relative reassessment as AI attention rises. Long-standing relationship lenders exhibit no such differential. These results point to industry-specific expertise as an important source of heterogeneity in how lenders interpret exposure to a new technology.

The industry-level reassessment also masks changes in the relative assessment of competitors. Within product markets, firms that occupied stronger pre-ChatGPT market positions experience a relative deterioration in assessed credit risk as AI attention rises in highly AI-

exposed markets. The effect becomes larger toward the top of the pre-ChatGPT market hierarchy. Thus, banks' response to AI is not limited to changing their assessment of exposed industries as a whole; it also changes the relative risk they assign to firms competing within those industries.

The same within-market pattern appears in credit outcomes. As AI attention rises, firms near the top of highly AI-exposed markets experience less drawn and committed credit, fewer lending relationships, and less favorable lender matching relative to lower-ranked competitors, compared with the corresponding changes in other markets. The market-position pattern also appears in subsequent repayment performance: the relative advantage of higher-ranked firms in avoiding bad-credit events narrows in highly AI-exposed markets as AI attention rises, even conditional on banks' contemporaneous consensus PD.

Technological change can therefore affect financing conditions before its real effects are fully realized, as financial intermediaries form and act on expectations about which firms are most likely to benefit or lose. The financing consequences of AI may thus depend not only on firms' technological exposure, but also on how banks interpret that exposure and on the information they bring to that assessment.

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Figure 1: Public attention to AI over time

This figure plots the two indices of public attention to artificial intelligence used in the analysis over 2021Q1–2024Q4. The Google Trends index aggregates monthly search intensity for AI-related queries to the quarter; the Wikipedia index is the quarterly volume of pageviews for AI-related articles in each country's language. Each index is standardized to zero mean and unit standard deviation within the country panel; the figure displays the average across the four sample countries (Germany, France, Italy, and Spain), while the country×quarter series enter the regressions. The vertical dashed line marks the public release of ChatGPT in 2022Q4.

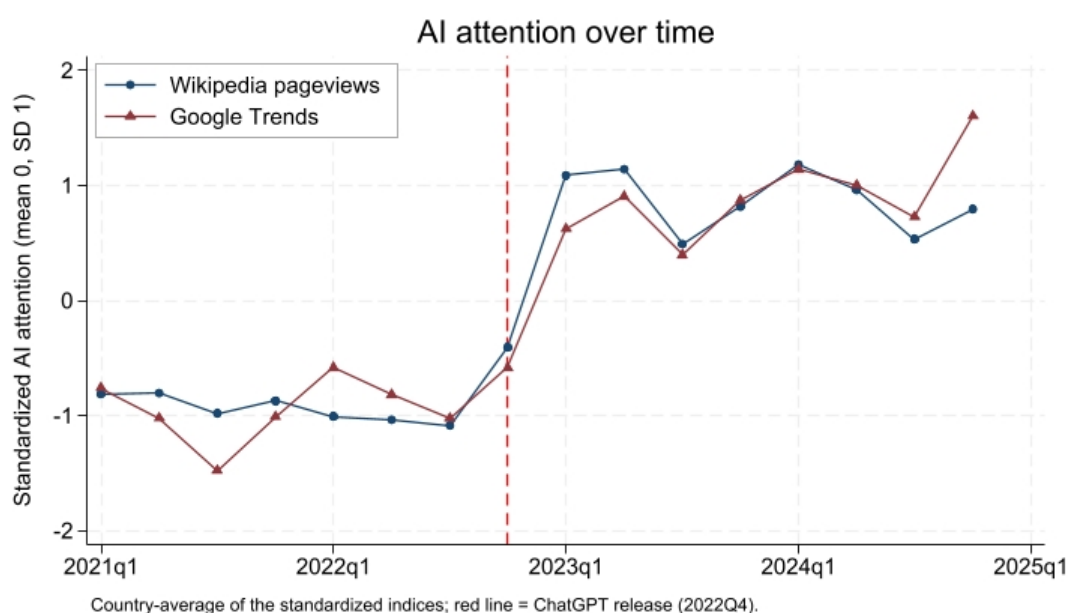


Figure 2: Expert and relationship lenders' relative PD assessment of high-AI borrowers

Coefficients on *High AI exposure* $\times$ lender indicator $\times$ quarter dummies (reference quarter 2022Q3) from regressions of $\ln(PD)$ with firm $\times$ quarter and bank $\times$ country $\times$ quarter fixed effects and the bank–firm controls of Table 4, estimated on the samples of its columns 1 (Panel A) and 2 (Panel B). Both lender attributes are measured in 2022Q3: an *expert lender* has a loan-portfolio weight of at least 10% in the borrower's NACE 2-digit industry, and a *relationship lender* has a lending relationship with the borrower exceeding three years. Negative values mean the lender type assigns lower PDs to high-AI borrowers than co-lenders of the same firm in the same quarter. Vertical bars are 95% confidence intervals (standard errors double-clustered by firm and bank); the dashed line marks the 2022Q3 baseline and the short-dashed line the ChatGPT quarter (2022Q4).

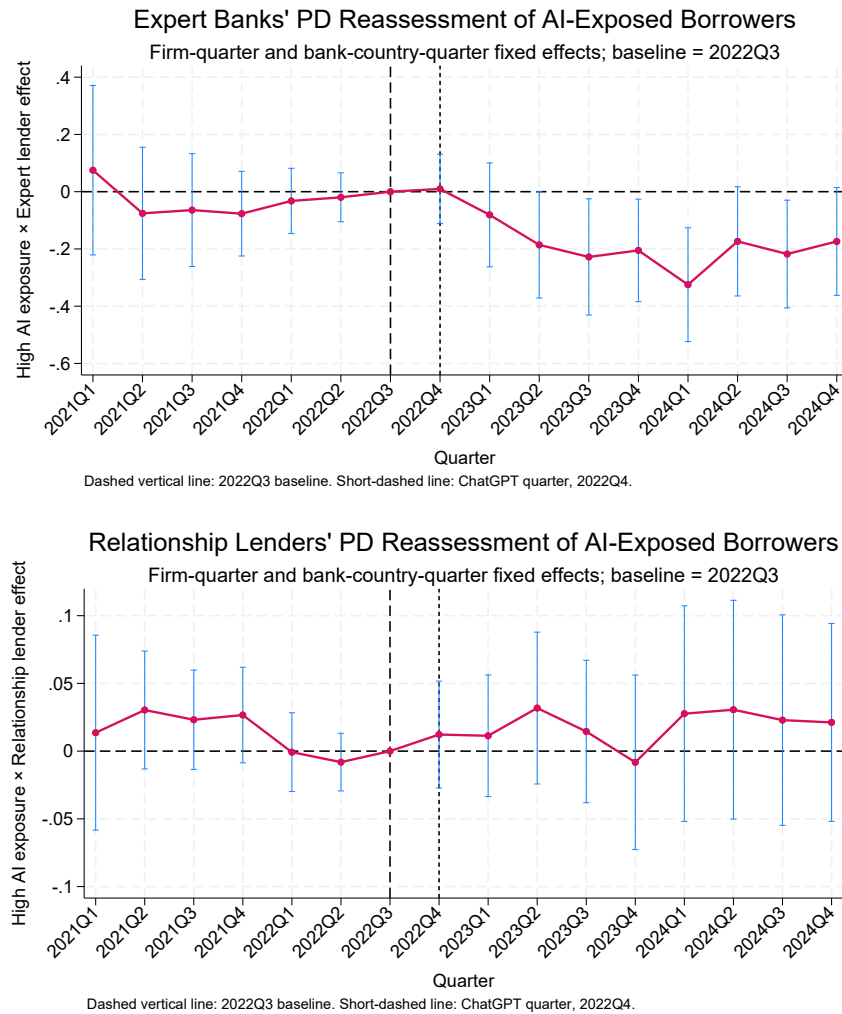


Figure 3: Within-market event-study coefficients around ChatGPT

This figure plots quarterly coefficients on *Incumbency rank* $\times$ *High AI exposure*, relative to 2022Q3, from the baseline specification of Table 6 with the full set of controls; $N = 5,906,989$. Hollow markers denote pre-ChatGPT quarters and filled markers post-ChatGPT quarters. Whiskers are 95% confidence intervals based on standard errors double-clustered by firm and bank. The vertical reference date is the public release of ChatGPT in 2022Q4.

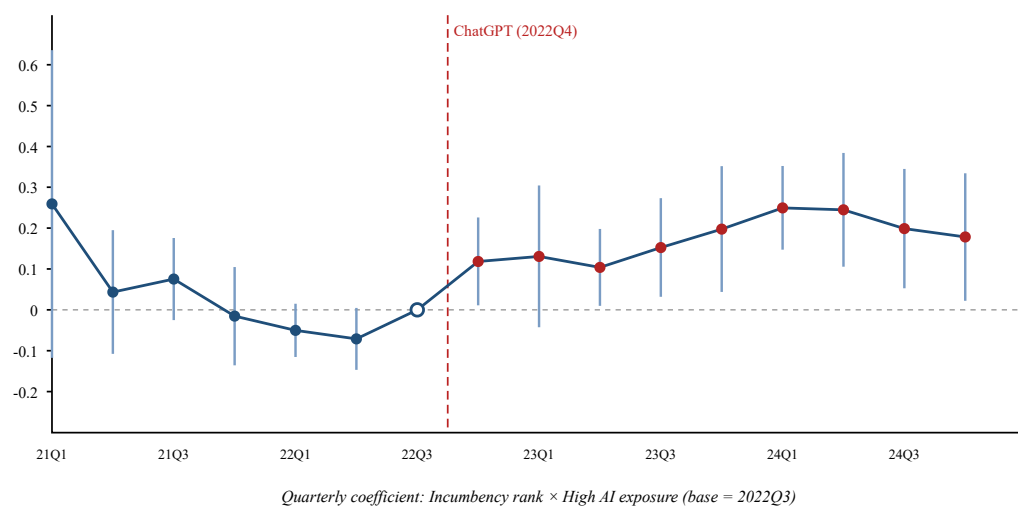


Figure 4: The AI reassessment across the market hierarchy

This figure plots coefficients on pre-shock position-decile $\times$ High AI exposure $\times$ AI attention (Google index), relative to the bottom decile of each market (hollow marker), from the specification of Table 6 with the full control sets on the ranked sample; whiskers are 95% confidence intervals based on standard errors double-clustered by firm and bank.

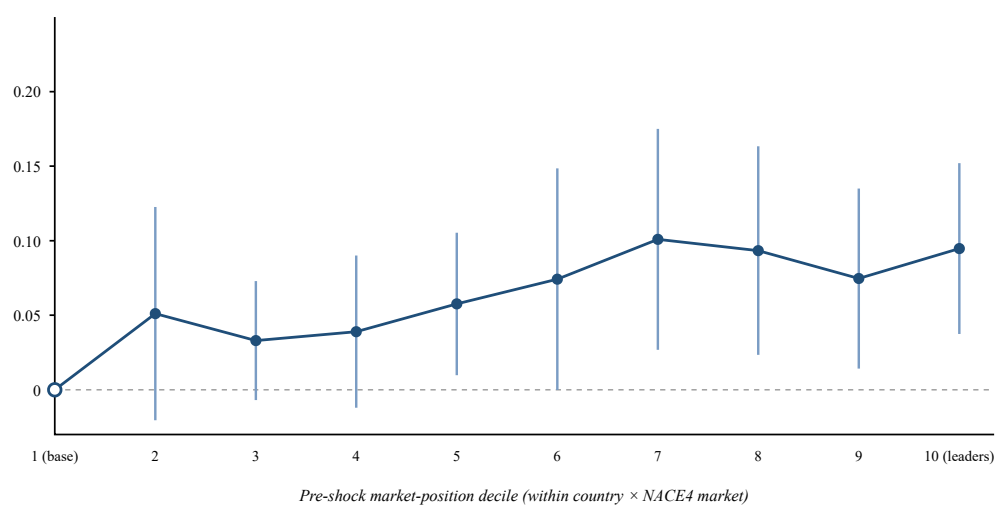


Figure 5: Credit quantities and lender matching

This figure plots coefficients on *Incumbency rank* $\times$ *High AI* $\times$ *AI attention* using the Google attention index, as reported in Table 7, with 95% confidence intervals. The left panel reports estimates for total drawn credit, the number of banking relationships, drawn credit per relationship, and total committed credit. The right panel reports estimates for the probability that an existing lending relationship terminates and the probability that the firm adds a new lender.

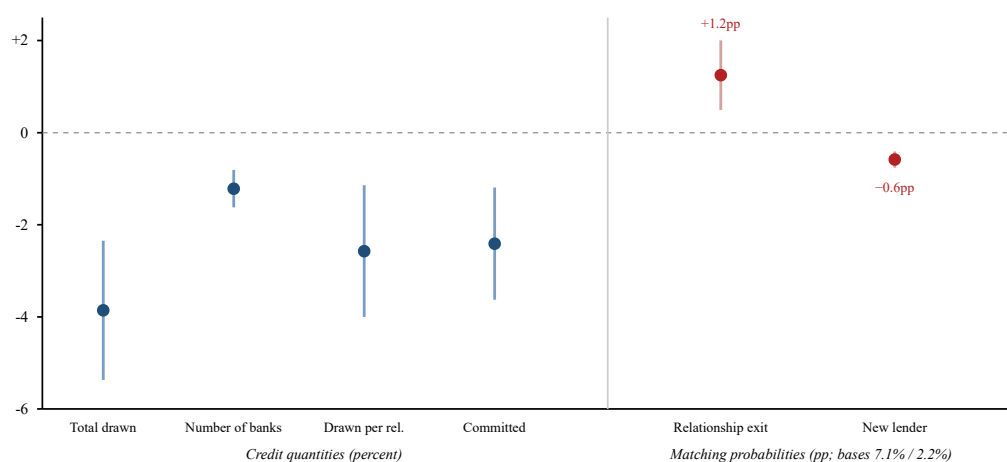


Table 1: Summary statistics

This table reports summary statistics for the main variables used in the analysis. The sample is a firm–bank–quarter panel of euro-area corporate credit exposures from AnaCredit, covering Germany, France, Italy, and Spain over 2021Q1–2024Q4. For each variable we report the number of observations (N), the mean, the standard deviation (SD), and the 25th, 50th (median), and 75th percentiles. Probability of default (PD) and interest rates are expressed as decimals (e.g., $0.027 = 2.7\%$). The AI-exposure measures are defined in Table A.1; standardized variants are normalized to zero mean and unit standard deviation over the estimation panel. Bank–firm relationship controls are measured at the end of the previous quarter; firm fundamentals are from Orbis. Detailed variable definitions are in Table A.2.

Variable	N	Mean	SD	p25	Median	p75
<i>Outcome variables</i>						
Probability of default (PD)	12,954,525	0.027	0.062	0.003	0.008	0.022
ln(PD)	12,954,525	−4.819	1.782	−5.776	−4.792	−3.822
<i>AI-exposure measures (native scale)</i>						
AIIE-LM	12,954,525	−0.118	0.870	−0.729	−0.202	0.523
AIIE-BR	12,954,525	−0.185	0.874	−0.808	−0.265	0.142
Eloundou	11,244,783	0.332	0.108	0.238	0.312	0.418
ESTZ	11,239,995	0.259	0.099	0.188	0.230	0.351
<i>AI-exposure measures (standardized)</i>						
AIIE-LM (std.)	12,954,525	0.000	1.000	−0.702	−0.097	0.737
AIIE-BR (std.)	12,954,525	0.000	1.000	−0.713	−0.092	0.374
Eloundou (std.)	11,244,783	0.000	1.000	−0.870	−0.185	0.796
ESTZ (std.)	11,239,995	0.000	1.000	−0.717	−0.293	0.929
<i>Control variables</i>						
Relationship length (years)	12,952,928	5.142	5.594	2	3	6
Bank share of firm credit	12,572,267	0.583	0.387	0.196	0.603	1.000
ln(committed exposure)	12,951,981	12.373	1.411	11.335	12.206	13.200
Undrawn share of commitment	12,951,981	0.236	0.340	0.000	0.033	0.372
ln(total assets)	12,954,525	14.223	1.532	13.215	14.089	15.083
ln(employees)	8,451,930	2.485	1.193	1.609	2.398	3.178
EBIT / total assets	10,272,595	0.051	0.108	0.011	0.039	0.090
Cash / total assets	12,545,584	0.158	0.168	0.027	0.098	0.238
Long-term debt / total assets	12,664,652	0.199	0.213	0.023	0.138	0.295
Firm age (years)	12,950,051	20.923	14.645	9	18	30

Table 2: Borrower AI exposure, public AI attention, and bank credit-risk assessment

This table reports estimates of bank-borrower probability-of-default (PD) assessments on the interaction of industry AI exposure with public AI attention, in a firm–bank–quarter panel of euro-area credit exposures over 2021Q1–2024Q4. In columns 1–4 the dependent variable $\ln(PD)$ is the natural log of the probability of default the bank reports for the firm in AnaCredit; in columns 5–8 it is the *portfolio PD rank*, the percentile of the borrower’s PD within the bank’s country portfolio in the quarter (for bank×country×quarter groups with at least 20 borrowers). The Felten–Raj–Seamans score (the 2023 language-modeling AIIE-LM baseline and the 2021 broad variant in the appendix) is a single cross-section per NACE2 industry. *High AI exposure* is an indicator that equals one if the borrower’s industry’s score is in the top sample quartile. *AI attention* is the standardized country–quarter index of public AI attention, from Google Trends (odd columns) and Wikipedia (even columns). Columns 1–2 and 5–6 include firm fixed effects; columns 3–4 and 7–8 replace them with firm–bank pair fixed effects, so estimates are identified within continuing lending relationships. All columns include bank×country×quarter fixed effects, bank–firm controls, and firm-level (Orbis) controls. Estimates with the standardized continuous exposure measure are in Appendix Table A.4. *t*-statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	ln(PD)				Portfolio PD rank			
	Firm FE		Firm×Bank FE		Firm FE		Firm×Bank FE	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)	Google (7)	Wiki (8)
High AI exposure × AI attention	−0.054** (−2.41)	−0.052** (−2.28)	−0.052** (−2.25)	−0.050** (−2.15)	−0.011*** (−3.56)	−0.010*** (−4.09)	−0.010*** (−3.40)	−0.010*** (−3.98)
N	6,839,622	6,839,622	6,808,992	6,808,992	6,834,266	6,834,266	6,803,722	6,803,722
Firm FE	Y	Y	N	N	Y	Y	N	N
Firm×Bank FE	N	N	Y	Y	N	N	Y	Y
Bank×Country×Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank–firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm (Orbis) controls	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.611	0.611	0.741	0.741	0.620	0.620	0.739	0.739

Table 3: The average reassessment: alternative exposure measures

This table re-estimates the baseline association of Table 2 using four alternative measures of industry AI exposure, defined in Table A.1. Columns 1–6 use top-quartile indicators of the Eloundou, Calvino, and ESTZ measures; columns 7–8 use the top-quartile indicator of the AIIIE-broad score of Felten, Raj, and Seamans (2021) and columns 9–10 its standardized continuous form. The dependent variable is $\ln(PD)$ in Panel A and the portfolio PD rank of Table 2 in Panel B. Each measure is assigned at the firm's modal NACE 2-digit industry; uninteracted terms are absorbed by the fixed effects. Samples follow each measure's coverage: the Eloundou and ESTZ occupational crosswalk covers 63 of the 81 NACE 2-digit divisions in the panel, and the Calvino taxonomy covers 66. All specifications are estimated within continuing lending relationships, with firm–bank pair and bank×country×quarter fixed effects, bank–firm controls, and Orbis fundamentals. t -statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

<i>Panel A: $\ln(PD)$</i>										
	Eloundou		Calvino		ESTZ		AIIIE-broad		z(AIIIE-broad)	
	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exposure × AI attention	−0.035*** (−2.65)	−0.032*** (−2.99)	−0.023* (−1.93)	−0.021** (−2.25)	−0.034*** (−2.75)	−0.031*** (−3.17)	−0.052*** (−2.23)	−0.051** (−2.12)	−0.008** (−2.30)	−0.009*** (−2.75)
N	6,113,967	6,113,967	6,217,070	6,217,070	6,113,967	6,113,967	6,808,992	6,808,992	6,808,992	6,808,992
Firm×Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank×Country×Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank–firm and Orbis controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.741	0.741	0.740	0.740	0.741	0.741	0.741	0.741	0.741	0.741
<i>Panel B: portfolio PD rank</i>										
	Eloundou		Calvino		ESTZ		AIIIE-broad		z(AIIIE-broad)	
	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki

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Table 3, continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exposure $\times$ AI attention	-0.008*** (-2.72)	-0.007*** (-3.11)	-0.006** (-2.00)	-0.005** (-2.03)	-0.008*** (-2.76)	-0.007*** (-3.08)	-0.010*** (-3.27)	-0.009*** (-3.75)	-0.001* (-1.80)	-0.002** (-2.29)
N	6,109,528	6,109,528	6,212,366	6,212,366	6,109,528	6,109,528	6,803,722	6,803,722	6,803,722	6,803,722
Firm $\times$ Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank $\times$ Country $\times$ Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank-firm and Orbis controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R ²	0.739	0.739	0.741	0.741	0.739	0.739	0.739	0.739	0.739	0.739

Table 4: Lender information and the assessment of AI-exposed borrowers

This table examines whether cross-lender differences in the assessment of AI-exposed borrowers are related to lender information, in the firm–bank–quarter panel restricted to multi-lender firms. Because all specifications include firm×quarter fixed effects, coefficients are identified purely from differences across banks lending to the same firm in the same quarter. Both lender attributes are measured before the attention shock, so that neither can respond to it. An *Industry expert* is a bank whose pre-ChatGPT (2022Q3) loan-portfolio weight in the borrower’s NACE 2-digit industry is at least 10%; a *Relationship lender* is a bank whose lending relationship with the borrower exceeded three years in 2022Q3, and the indicator is held at that value in every quarter. Columns 2–3 and 5–6 are therefore restricted to bank–firm pairs observed in 2022Q3. *AI attention* (abbreviated Attention in the row labels) is from Google Trends in columns 1–3 and Wikipedia in columns 4–6. The dependent variable is $\ln(PD)$ in Panel A and the portfolio PD rank of Table 2 in Panel B. All columns include bank×country×quarter fixed effects and bank–firm controls; firm-level controls are absorbed by the firm×quarter fixed effects. *t*-statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

Panel A: $\ln(PD)$

	Google attention			Wiki attention		
	(1)	(2)	(3)	(4)	(5)	(6)
High AI exp. × Attention × Industry expert	−0.117** (−2.40)		−0.114** (−2.08)	−0.173*** (−3.56)		−0.164*** (−2.99)
High AI exp. × Attention × Relationship lender		0.004 (0.32)	0.004 (0.30)		0.009 (0.60)	0.009 (0.59)
High AI exp. × Industry expert	−0.076 (−0.82)		−0.080 (−0.79)	−0.081 (−0.94)		−0.090 (−0.95)
Industry expert × Attention	0.052** (2.08)		0.045 (1.46)	0.058*** (2.66)		0.051* (1.82)
Industry expert	−0.010 (−0.36)		−0.010 (−0.27)	−0.013 (−0.51)		−0.013 (−0.37)
High AI exp. × Relationship lender		0.014 (0.66)	0.014 (0.67)		0.014 (0.69)	0.014 (0.71)
Relationship lender × Attention		−0.004 (−0.48)	−0.004 (−0.48)		−0.002 (−0.24)	−0.002 (−0.23)
Relationship lender		−0.026**	−0.026**		−0.025**	−0.025**

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Table 4, continued

		(−2.37)	(−2.37)		(−2.30)	(−2.31)
N	3,910,030	3,239,166	3,239,166	3,910,030	3,239,166	3,239,166
Firm×Qtr FE	Y	Y	Y	Y	Y	Y
Bank×Country×Qtr FE	Y	Y	Y	Y	Y	Y
Bank–firm controls	Y	Y	Y	Y	Y	Y
R^2	0.659	0.657	0.657	0.659	0.657	0.657

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Table 4, continued

Panel B: portfolio PD rank

	Google attention			Wiki attention		
	(1)	(2)	(3)	(4)	(5)	(6)
High AI exp. $\times$ Attention $\times$ Industry expert	-0.026** (-2.58)		-0.025** (-2.15)	-0.040*** (-3.96)		-0.037*** (-3.21)
High AI exp. $\times$ Attention $\times$ Relationship lender		-0.001 (-0.55)	-0.001 (-0.56)		-0.000 (-0.09)	-0.000 (-0.09)
High AI exp. $\times$ Industry expert	-0.033* (-1.81)		-0.037* (-1.85)	-0.034** (-2.04)		-0.039** (-2.12)
Industry expert $\times$ Attention	0.014** (2.46)		0.014* (1.86)	0.017*** (3.23)		0.017** (2.44)
Industry expert	0.006 (0.79)		0.006 (0.56)	0.005 (0.76)		0.005 (0.55)
High AI exp. $\times$ Relationship lender		0.002 (0.58)	0.002 (0.58)		0.002 (0.63)	0.002 (0.65)
Relationship lender $\times$ Attention		-0.001 (-0.44)	-0.001 (-0.43)		-0.000 (-0.04)	-0.000 (-0.02)
Relationship lender		-0.004* (-1.84)	-0.004* (-1.84)		-0.004* (-1.77)	-0.004* (-1.76)
N	3,905,568	3,236,445	3,236,445	3,905,568	3,236,445	3,236,445
Firm $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
Bank $\times$ Country $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
Bank-firm controls	Y	Y	Y	Y	Y	Y
R^2	0.683	0.693	0.693	0.683	0.693	0.693

Table 5: Labor intensity and the average reassessment

This table presents the regressions in the baseline Table 2 adding an interaction with labor intensity. *Labor intensity* is the borrower's pre-ChatGPT (through 2022Q2) employees per unit of operating revenue, held fixed at the firm level; columns 1–2 and 5–6 use an above-median indicator (*High labor intensity*) and columns 3–4 and 7–8 the standardized continuous measure. The dependent variable is $\ln(PD)$ in columns 1–4 and the portfolio PD rank in columns 5–8. All columns are estimated within continuing lending relationships, with firm–bank pair and bank×country×quarter fixed effects; the firm-fixed-effects counterpart is in Appendix Table A.7. The same set of control variables from Table 2 are included. *t*-statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	ln(PD)				Portfolio PD rank			
	High labor intensity		z(Labor intensity)		High labor intensity		z(Labor intensity)	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)	Google (7)	Wiki (8)
High AI exposure × AI attention	−0.071** (−2.41)	−0.071** (−2.23)	−0.049** (−2.11)	−0.049** (−2.06)	−0.014*** (−3.43)	−0.013*** (−3.83)	−0.009*** (−3.26)	−0.009*** (−3.97)
High AI × AI attention × Labor intensity	0.042*** (3.06)	0.041** (2.50)	0.023*** (3.21)	0.022*** (2.72)	0.008*** (3.15)	0.008*** (2.89)	0.004*** (3.16)	0.004*** (3.19)
AI attention × Labor intensity	−0.021** (−1.98)	−0.019* (−1.71)	−0.013** (−2.34)	−0.012* (−1.91)	−0.008*** (−3.25)	−0.007*** (−2.94)	−0.005*** (−3.42)	−0.004*** (−3.21)
N	6,368,090	6,368,090	6,368,090	6,368,090	6,363,575	6,363,575	6,363,575	6,363,575
Firm×Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank×Country×Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank–firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm (Orbis) controls	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733

Table 6: Within-market re-ranking of firms in AI-exposed markets

This table asks whether banks re-rank firms within the same product market as AI attention rises. A *market* is a country×NACE 4-digit cell with at least 20 firms in the Orbis universe (NACE 3-digit in columns 3–4). *Incumbency rank* is the firm’s within-market percentile of mean fiscal 2019–2021 sales (0 = smallest, 1 = market leader), computed among positive-sales firms and held fixed throughout. Panel A uses $\ln(PD)$; Panel B uses the *within-market PD rank*, the firm’s PD percentile within its bank×market×quarter cell (cells with at least 5 borrowers) — whereas the portfolio PD rank of Table 2 measures position in the bank’s overall book, the within-market rank measures position among direct product-market peers. All columns include firm×bank pair and bank×market×quarter fixed effects, which absorb the High AI × AI attention term of Table 2, all exposure and attention main effects, and every market-wide shock, so identification comes from the same bank re-ranking differently positioned firms within the same market; positive coefficients indicate that higher-ranked incumbents’ assessed risk deteriorates relative to lower-ranked competitors. Columns 5–6 add size-decile×country×quarter fixed effects and columns 7–8 add pre-ChatGPT PD-decile×country×quarter fixed effects; bank–firm and firm-level controls are included throughout. *t*-statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	Baseline (NACE4)		NACE3 markets		+ Size-dec.×Ctry×Qtr		+ PD-dec.×Ctry×Qtr	
	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: $\ln(PD)$</i>								
Incumbency rank × High AI × Attention	0.074**	0.075**	0.070**	0.072**	0.059***	0.064***	0.082**	0.082**
	(2.41)	(2.29)	(2.17)	(2.21)	(2.61)	(2.66)	(2.54)	(2.45)
Incumbency rank × Attention	0.081	0.077	0.085	0.080	0.167	0.154	0.044	0.042
	(0.60)	(0.61)	(0.61)	(0.62)	(1.08)	(1.01)	(0.35)	(0.37)
N	5,906,989	5,906,989	5,909,822	5,909,822	5,677,333	5,677,333	5,677,333	5,677,333
R^2	0.745	0.745	0.745	0.745	0.741	0.741	0.744	0.744
<i>Panel B: within-market PD rank</i>								
Incumbency rank × High AI × Attention	0.011**	0.012**	0.010*	0.011*	0.012*	0.013**	0.013**	0.014**
	(2.06)	(2.04)	(1.81)	(1.88)	(1.92)	(2.02)	(2.57)	(2.48)
Incumbency rank × Attention	0.026	0.024	0.028	0.025	0.037**	0.034*	0.016	0.015
	(1.51)	(1.44)	(1.55)	(1.47)	(2.01)	(1.86)	(1.18)	(1.21)
N	5,714,954	5,714,954	5,715,498	5,715,498	5,499,059	5,499,059	5,499,059	5,499,059
R^2	0.689	0.689	0.689	0.689	0.686	0.686	0.693	0.693
Firm×Bank (pair) FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank×Market×Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Size-decile×Ctry×Qtr FE	N	N	N	N	Y	Y	N	N
PD-decile×Ctry×Qtr FE	N	N	N	N	N	N	Y	Y
Bank–firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y

Table 7: Credit quantities and lender matching

This table asks whether the within-market re-ranking of Table 6 moves actual credit. In Panel A the unit of observation is the firm-quarter and the dependent variables are the log of total drawn credit summed across banks, the log number of banking relationships, and the log of drawn credit per relationship; on the common sample the latter two decompose the first. Panel B tests the matching margin: the probability that an existing bank relationship is not observed in the following quarter (quarterly base rate 7.1%), the probability that the firm attracts a new lender in the following quarter (base rate 2.2%), and the log of total committed capacity (drawn plus undrawn). Exit is estimated at the firm-bank-quarter level with firm and bank $\times$ quarter fixed effects and both control sets. The remaining columns are firm-quarter regressions with firm and market $\times$ quarter fixed effects. Firm-level controls use the coverage-preserving tier (ln assets, cash/assets, long-term debt/assets). t -statistics in parentheses; Panel A and Panel B columns 3–6 cluster by firm, Panel B columns 1–2 double-cluster by firm and bank; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

Panel A: firm-level credit and its margins

	ln total drawn		ln number of banks		ln drawn per relationship	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)
Incumbency rank $\times$ High AI $\times$ Attention	-0.039*** (-5.01)	-0.039*** (-5.63)	-0.012*** (-5.87)	-0.015*** (-7.85)	-0.026*** (-3.52)	-0.024*** (-3.60)
Incumbency rank $\times$ Attention	0.013*** (3.19)	0.016*** (4.45)	0.011*** (9.17)	0.015*** (14.75)	0.002 (0.50)	0.000 (0.06)

N	4,013,694	4,013,694	4,143,125	4,143,125	4,013,694	4,013,694
Firm controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Market $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
R^2	0.893	0.893	0.847	0.847	0.883	0.883

Panel B: the matching margin and committed capacity

continued on next page

Table 7, continued

	P(relationship exits at $t+1$)		P(new lender at $t+1$)		ln total committed	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)
Incumbency rank $\times$ High AI $\times$ Attention	0.012*** (3.24)	0.009*** (2.73)	-0.006*** (-6.54)	-0.007*** (-9.03)	-0.024*** (-3.88)	-0.026*** (-4.59)
Incumbency rank $\times$ Attention	-0.044*** (-8.64)	-0.036*** (-8.26)	0.014*** (26.47)	0.017*** (35.50)	0.016*** (5.03)	0.017*** (5.86)
N	5,626,587	5,626,587	3,931,035	3,931,035	4,142,311	4,142,311
Firm controls	Y	Y	Y	Y	Y	Y
Bank-firm controls	Y	Y	N	N	N	N
Firm FE	Y	Y	Y	Y	Y	Y
Bank $\times$ Market $\times$ Qtr FE	Y	Y	N	N	N	N
Market $\times$ Qtr FE	N	N	Y	Y	Y	Y
R^2	0.313	0.313	0.129	0.129	0.928	0.928

Table 8: Outcome validation

This table examines whether the market-position pattern in banks' PD assessments is also present in subsequent credit performance. The dependent variable in columns 1–3 and 5–7 is an indicator for a bad-credit event in any of quarters $t + 1$ through $t + 4$ (supervisory forward file; sample mean 8.2%), estimated through 2023Q4 so the outcome window closes within the data; columns 4 and 8 use bad status at exactly $t + 1$ (mean 3.0%), which extends the sample through 2024Q3. Regressions are at the firm–quarter level and include *incumbency rank* $\times$ *High AI* $\times$ *AI attention*, without the consensus $\ln(PD)$ in columns 1 and 5 and conditional on it elsewhere. Columns 3 and 7 add profitability to the control set. Columns 1–4 use Google attention and columns 5–8 Wikipedia attention. All columns include firm and market $\times$ quarter fixed effects and firm-level controls. t -statistics (standard errors clustered by NACE 2-digit industry) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	Google attention				Wikipedia attention			
	No consensus (1)	Baseline (2)	+ Profitability (3)	Bad at $t+1$ (4)	No consensus (5)	Baseline (6)	+ Profitability (7)	Bad at $t+1$ (8)
Incumbency rank $\times$ High AI $\times$ Attention	0.007*** (2.62)	0.007** (2.56)	0.007** (2.21)	0.005** (2.41)	0.005** (2.09)	0.005** (2.01)	0.004* (1.73)	0.004** (2.28)
Incumbency rank $\times$ Attention	−0.013*** (−7.16)	−0.013*** (−7.28)	−0.014*** (−6.93)	−0.008*** (−5.60)	−0.010*** (−6.05)	−0.010*** (−6.17)	−0.011*** (−5.93)	−0.006*** (−5.60)
Consensus $\ln(PD)$		0.002*** (6.89)	0.002*** (6.63)	0.002*** (7.70)		0.002*** (6.90)	0.002*** (6.65)	0.002*** (7.69)
N	3,269,411	3,269,411	2,918,361	3,696,069	3,269,411	3,269,411	2,918,361	3,696,069
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Market $\times$ Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Profitability control	N	N	Y	N	N	N	Y	N
R^2	0.614	0.614	0.621	0.381	0.614	0.614	0.621	0.381

Appendix

Table A.1: Most and least AI-exposed industries

This table lists the five most and five least AI-exposed industries (NACE 2-digit) under each of the four industry-level AI-exposure measures used in the paper: the language-modeling score of Felten, Raj, and Seamans (2023) (*AIIE-LM*, the baseline), their broad score (2021) (*AIIE-BR*), the large-language-model exposure of Eloundou et al. (2024), and the generative-AI exposure of Eisfeldt, Schubert, Taska, and Zhang (*ESTZ*). For each industry we report its NACE 2-digit code, a short description, and its tier in the AI-intensity taxonomy of Calvino et al. (2024); “Unclass.” denotes industries outside that taxonomy’s scope. Rankings are computed over the industries present in the estimation sample.

AIIE-LM				AIIE-BR			
Rank	NACE	Industry	Calvino tier	Rank	NACE	Industry	Calvino tier
<i>Five most exposed</i>							
1	69	Legal & accounting	High	1	69	Legal & accounting	High
2	62	Computer programming & consult.	High	2	62	Computer programming & consult.	High
3	63	Information services	High	3	63	Information services	High
4	79	Travel agencies & tour ops.	Medium	4	72	Scientific R&D	High
5	58	Publishing	High	5	58	Publishing	High
<i>Five least exposed</i>							
1	2	Forestry & logging	Unclass.	1	1	Agriculture (crop & animal)	Unclass.
2	1	Agriculture (crop & animal)	Unclass.	2	81	Building & landscape services	Medium
3	43	Specialised construction	Low	3	43	Specialised construction	Low
4	81	Building & landscape services	Medium	4	2	Forestry & logging	Unclass.
5	16	Wood products	Low	5	3	Fishing & aquaculture	Unclass.
Eloundou				ESTZ			
Rank	NACE	Industry	Calvino tier	Rank	NACE	Industry	Calvino tier
<i>Five most exposed</i>							
1	62	Computer programming & consult.	High	1	69	Legal & accounting	High
2	63	Information services	High	2	79	Travel agencies & tour ops.	Medium
3	69	Legal & accounting	High	3	63	Information services	High
4	79	Travel agencies & tour ops.	Medium	4	62	Computer programming & consult.	High
5	72	Scientific R&D	High	5	70	Head offices & consultancy	High
<i>Five least exposed</i>							
1	81	Building & landscape services	Medium	1	81	Building & landscape services	Medium
2	56	Food & beverage services	Low	2	56	Food & beverage services	Low
3	15	Leather products	Low	3	43	Specialised construction	Low
4	17	Paper products	Low	4	96	Other personal services	Unclass.
5	16	Wood products	Low	5	15	Leather products	Low

Table A.2: Variable definitions

Variable	Definition
<i>Panel A. Probabilities of default (bank–firm–quarter)</i>	
<i>PD</i>	Bank’s internal probability of default for the borrower in the current quarter (AnaCredit).
$\ln PD$	Natural logarithm of <i>PD</i> , bounded to $(10^{-6}, 1 - 10^{-6})$.
Portfolio PD rank	Percentile of $\ln PD$ within the bank’s country portfolio in the quarter (bank×country×quarter cells with ≥ 20 borrowers).
<i>Panel B. AI exposure and attention (industry / country)</i>	
AIIE-LM	Industry (NACE-2) AI occupational-exposure index, language-modeling variant, from Felten, Raj, and Seamans (2023); the paper’s baseline measure. Assigned to each firm at its modal NACE-2 code.
High-AI	Indicator equal to one if the firm’s (time-invariant, modal-industry) AIIE-LM lies strictly above the 75th percentile of the estimation panel’s observation-level distribution, computed once on the full filtered panel and held fixed across all specifications — the industries carrying the top quarter of credit exposures.
AIIE-broad	Broad AI occupational-exposure index from Felten, Raj, and Seamans (2021).
Eloundou	Occupational GPT-exposure share from Eloundou et al. (2024), aggregated to NACE-2.
ESTZ	Generative-AI workforce exposure from Eisfeldt, Schubert, Taska, and Zhang, aggregated to NACE-2.
Calvino tier	OECD AI-intensity tier (1 = Low to 3 = High) from Calvino et al. (2024).

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Table A.2, continued

Variable	Definition
AI attention (GT)	Standardized (mean 0, s.d. 1) country–quarter log Google Trends search intensity for “AI” and “ChatGPT.”
AI attention (Wiki)	Standardized country–quarter log Wikipedia pageviews for AI-related articles in the country’s language.
<i>Panel C. Bank expertise and relationship (bank–firm)</i>	
Expert	Indicator equal to one if, in the pre-ChatGPT window ($\leq 2022Q3$), the bank’s loan-portfolio share in the borrower’s NACE-2 industry is at least 10%.
Expertise intensity	The bank’s pre-ChatGPT (log) loan-portfolio share in the borrower’s NACE-2 industry, standardized across bank–industry pairs.
Relationship	Indicator equal to one if the bank–borrower lending relationship is longer than three years in 2022Q3, held at that value in every quarter.
<i>Panel D. Firm characteristics (Orbis)</i>	
Total assets	Natural logarithm of total assets.
Employees	Natural logarithm of one plus the number of employees.
Profitability	EBIT divided by total assets.
Cash	Cash and equivalents divided by total assets.
Leverage	Long-term debt divided by total assets.
Firm age	Years since incorporation.
Labor intensity	Borrower’s number of employees divided by operating revenue, measured pre-ChatGPT ($\leq 2022Q2$) and held fixed at the firm level; standardized (in logs) in the continuous specification. From <i>Orbis</i> .
High labor intensity	Indicator equal to one if <i>Labor intensity</i> is above the sample median.

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Table A.2, continued

Variable	Definition
<i>Panel E. Loan and relationship controls (bank–firm, lagged one quarter)</i>	
Log commitment	Natural logarithm of the bank’s total committed exposure (drawn plus undrawn).
Undrawn share	Undrawn credit divided by total committed exposure.
Bank share	Bank’s share of the borrower’s total AnaCredit exposure.
Log relationship	Natural logarithm of one plus the relationship length (years).
<i>Panel F. Market structure and re-ranking variables</i>	
Market	Country $\times$ NACE 4-digit cell with ≥ 20 firms with positive sales in the Orbis universe (NACE 3-digit in robustness).
Incumbency rank	The firm’s within-market percentile of mean fiscal 2019–21 sales (0 = smallest, 1 = leader), computed among positive-sales universe firms and frozen pre-ChatGPT.
Alternative incumbency ranks	Same construction with 2019-only sales, or with mean employment, in place of mean 2019–21 sales (positive-value filter applied before ranking in each case).
Within-market PD rank	The firm’s percentile rank of $\ln PD$ within bank $\times$ market $\times$ quarter (cells with ≥ 5 borrowers).
Bad-credit event	Indicator for bad credit status in any of quarters $t+1..t+4$ (if the firm has arrears equal to or exceeding 1% of outstanding exposure with any bank or max days past due equal to or exceeding 90 days with any bank).
Relationship exit	Indicator: the bank–firm pair is not observed in $t+1$ (censored at sample end).
New lender	Indicator: any bank first observed lending to the firm in $t+1$.

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Table A.2, continued

Variable	Definition
Number of banks	Count of the firm's AnaCredit lenders in the quarter.
Drawn per relationship	Total drawn credit divided by the number of lenders.

Table A.3: Market-definition health

This table reports the number of Orbis-universe firms per market cell by country, at the NACE 4-digit and NACE 3-digit levels, before imposing the 20-firm floor used to construct the incumbency rank; the floor excludes 494 of 2,767 NACE 4-digit cells and 154 of 1,191 NACE 3-digit cells. In the credit panel, 6.77 million firm–bank–quarter observations match to a ranked firm; the median bank×market×quarter cell contains 124 borrowers, and the within-market PD rank is defined for 94% of ranked observations.

Country	NACE 4-digit			NACE 3-digit		
	Cells	Median firms	p25	Cells	Median firms	p25
DE	778	15	4	332	27	8
ES	607	83	27	267	183	39
FR	597	62	17	263	135	32
IT	785	51	9	329	87	12

Panel observations matched to a rank: 6.77M; median bank×market×quarter cell: 124 borrowers
(within-market PD-rank coverage 94%).

Table A.4: The average reassessment with continuous AI exposure

This table reports the specifications of Table 2 with the standardized continuous AI-exposure measure (*AI exposure*, the AIIE-LM score standardized over the estimation panel) in place of the top-quartile indicator, so coefficients are per standard deviation of exposure. Columns are arranged as in Table 2: $\ln(PD)$ in columns 1–4 and the portfolio PD rank in columns 5–8, with firm fixed effects in columns 1–2 and 5–6 and firm–bank pair fixed effects in columns 3–4 and 7–8. All columns include bank×country×quarter fixed effects, bank–firm controls, and firm-level (Orbis) controls. t -statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	$\ln(PD)$				Portfolio PD rank			
	Firm FE		Firm×Bank FE		Firm FE		Firm×Bank FE	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)	Google (7)	Wiki (8)
AI exposure × AI attention	−0.007** (−2.50)	−0.009*** (−3.18)	−0.007*** (−2.60)	−0.009*** (−3.45)	−0.001 (−1.46)	−0.001* (−1.75)	−0.001 (−1.47)	−0.001* (−1.78)
N	6,839,622	6,839,622	6,808,992	6,808,992	6,834,266	6,834,266	6,803,722	6,803,722
Firm FE	Y	Y	N	N	Y	Y	N	N
Firm×Bank FE	N	N	Y	Y	N	N	Y	Y
Bank×Country×Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank–firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm (Orbis) controls	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.611	0.611	0.741	0.741	0.620	0.620	0.739	0.739

Table A.5: Borrower AI exposure and cross-bank disagreement in credit-risk assessment

This table relates borrowers' industry AI exposure and public AI attention to cross-bank dispersion in PD assessments. The unit of observation is the firm-quarter, restricted to firms borrowing from at least two banks, over 2021Q1–2024Q4. The dependent variable is the cross-lender dispersion of the firm's assigned PD in the quarter: its standard deviation (columns 1–2), range (columns 3–4), and coefficient of variation (columns 5–6). *High AI exposure* equals one if the borrower's NACE 2-digit industry (fixed at the firm's modal industry) lies in the top quartile of AIIE-LM. *AI attention* is the standardized country-quarter public-attention index, from Google Trends and Wikipedia as labeled; the reported coefficient is on its interaction with *High AI exposure*. Because the standard deviation and range scale mechanically with the level of PD, columns 1–4 control for the firm's *Mean PD*; the scale-free coefficient of variation does not. All columns include firm and country×quarter fixed effects. *t*-statistics (standard errors clustered by firm) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	Cross-bank dispersion of PD					
	Std. deviation (pp)		Range (pp)		Coeff. of variation	
	Google	Wiki	Google	Wiki	Google	Wiki
<i>AI attention:</i>						
High AI exposure × AI attention	0.0293*** (5.127)	0.0268*** (4.940)	0.0418*** (4.254)	0.0372*** (3.992)	0.0064*** (4.352)	0.0049*** (3.561)
Mean PD	1.0100*** (363.0)	1.0100*** (363.0)	1.6300*** (344.6)	1.6300*** (344.6)		
Ln(number of lenders)	0.6920*** (47.28)	0.6920*** (47.27)	3.2100*** (105.7)	3.2100*** (105.7)	0.2660*** (78.94)	0.2660*** (78.93)
Ln(total assets)	-0.0460*** (-3.529)	-0.0462*** (-3.542)	-0.0494** (-2.225)	-0.0496** (-2.237)	-0.0116*** (-4.108)	-0.0116*** (-4.130)
Ln(employment)	0.0400*** (3.576)	0.0401*** (3.581)	0.0681*** (3.523)	0.0682*** (3.528)	-0.0131*** (-5.592)	-0.0131*** (-5.582)
EBIT/total assets	0.5150*** (13.81)	0.5150*** (13.81)	0.7480*** (11.90)	0.7480*** (11.90)	0.0313*** (3.952)	0.0313*** (3.947)
Cash/total assets	0.5350*** (20.58)	0.5340*** (20.57)	0.9020*** (20.24)	0.9010*** (20.22)	0.0890*** (12.30)	0.0888*** (12.27)
Long-term debt/total assets	-0.0820** (-2.381)	-0.0820** (-2.382)	-0.1380** (-2.340)	-0.1380** (-2.340)	0.0059 (0.843)	0.0059 (0.845)
Firm age	0.0041 (0.362)	0.0039 (0.342)	0.0319 (1.419)	0.0316 (1.403)	0.0023 (0.628)	0.0022 (0.609)
Firm FE	Y	Y	Y	Y	Y	Y
Country×Qtr FE	Y	Y	Y	Y	Y	Y
N	1,546,698	1,546,698	1,546,698	1,546,698	1,546,081	1,546,081
<i>R</i> ²	0.887	0.887	0.879	0.879	0.460	0.460

Table A.6: Specialization and relationship as continuous doses

This table re-estimates the lender-information specification of Table 4, replacing the two indicators with standardized continuous measures, both measured before the attention shock. $z(\text{Portfolio share})$ is the standardized log of the bank's pre-ChatGPT (2022Q3) portfolio weight in the borrower's NACE 2-digit industry, the continuous analog of the 10% expert indicator; $z(\text{Relationship length})$ is the standardized log of one plus the bank-borrower relationship length in years, measured in 2022Q3 and held at that value in every quarter, the continuous analog of the three-year indicator. Columns 2–3 and 5–6 are therefore restricted to bank-firm pairs observed in 2022Q3. Coefficients are per standard deviation. The dependent variable is $\ln(PD)$ in Panel A and the portfolio PD rank of Table 2 in Panel B. All columns include firm $\times$ quarter and bank $\times$ country $\times$ quarter fixed effects, bank-firm controls, and Orbis fundamentals; lower-order interactions and levels are included but suppressed for brevity. t -statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

Panel A: $\ln(PD)$

	Google AI attention			Wiki AI attention		
	(1)	(2)	(3)	(4)	(5)	(6)
High AI exp. $\times$ Attention $\times$ $z(\text{Portfolio share})$	−0.068*** (−2.86)		−0.060** (−2.43)	−0.109*** (−4.05)		−0.097*** (−3.59)
High AI exp. $\times$ Attention $\times$ $z(\text{Relationship length})$		−0.011* (−1.93)	−0.012** (−2.09)		−0.009 (−1.42)	−0.010 (−1.63)
N	3,906,836	3,239,134	3,238,837	3,906,836	3,239,134	3,238,837
Firm $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
Bank $\times$ Country $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
Bank-firm controls	Y	Y	Y	Y	Y	Y
Firm (Orbis) controls	Y	Y	Y	Y	Y	Y
R^2	0.659	0.657	0.657	0.659	0.657	0.657

Panel B: portfolio PD rank

	Google AI attention			Wiki AI attention		
	(1)	(2)	(3)	(4)	(5)	(6)
High AI exp. $\times$ Attention $\times$ $z(\text{Portfolio share})$	−0.014*** (−3.13)		−0.013** (−2.62)	−0.025*** (−4.81)		−0.022*** (−4.15)
High AI exp. $\times$ Attention $\times$ $z(\text{Relationship length})$		−0.002** (−2.01)	−0.002** (−2.12)		−0.002 (−1.44)	−0.002 (−1.61)
N	3,903,111	3,236,416	3,236,274	3,903,111	3,236,416	3,236,274
Firm $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
Bank $\times$ Country $\times$ Qtr FE	Y	Y	Y	Y	Y	Y
Bank-firm controls	Y	Y	Y	Y	Y	Y
Firm (Orbis) controls	Y	Y	Y	Y	Y	Y
R^2	0.683	0.693	0.693	0.683	0.693	0.683

Table A.7: Labor intensity with firm fixed effects

This table reports the firm-fixed-effects counterpart of Table 5. *Labor intensity* is the borrower's pre-ChatGPT (through 2022Q2) employees per unit of operating revenue, held fixed at the firm level; columns 1–2 and 5–6 use an above-median indicator (*High labor intensity*) and columns 3–4 and 7–8 the standardized continuous measure. The dependent variable is $\ln(PD)$ in columns 1–4 and the portfolio PD rank in columns 5–8. All columns include firm and bank $\times$ country $\times$ quarter fixed effects, bank–firm controls, and firm-level (Orbis) controls. *t*-statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	$\ln(PD)$				Portfolio PD rank			
	High labor intensity		z(Labor intensity)		High labor intensity		z(Labor intensity)	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)	Google (7)	Wiki (8)
High AI exposure $\times$ AI attention	−0.074** (−2.54)	−0.074** (−2.37)	−0.051** (−2.24)	−0.051** (−2.18)	−0.014*** (−3.53)	−0.014*** (−3.87)	−0.010*** (−3.37)	−0.009*** (−4.03)
High AI $\times$ AI attention $\times$ Labor intensity	0.044*** (3.11)	0.045*** (2.60)	0.025*** (3.37)	0.025*** (2.88)	0.008*** (3.08)	0.008*** (2.83)	0.004*** (3.19)	0.004*** (3.15)
AI attention $\times$ Labor intensity	−0.022** (−2.03)	−0.019 (−1.56)	−0.014** (−2.51)	−0.012* (−1.87)	−0.008*** (−3.46)	−0.007*** (−3.10)	−0.005*** (−3.72)	−0.004*** (−3.47)
N	6,394,669	6,394,669	6,394,669	6,394,669	6,390,077	6,390,077	6,390,077	6,390,077
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank $\times$ Country $\times$ Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank–firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm (Orbis) controls	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.600	0.600	0.600	0.600	0.611	0.611	0.611	0.611

Table A.8: Robustness of the within-market re-ranking

This table subjects the baseline specification of Table 6, column 1, to three batteries. Each column reports a separate regression; columns headed Google and Wiki interact the same exposure and rank terms with the Google Trends or Wikipedia attention index, respectively. Panels A and B replace the AIIE-LM classification with four alternative exposure measures (defined in Table A.1): Panel A uses top-quartile indicators, matching Table 6 exactly, and Panel B enters each measure continuously, so coefficients are per standard deviation of exposure. The memo row re-estimates the baseline AIIE-LM triple on each column's own estimation sample under that column's attention index, separating measurement differences from coverage differences; the Eloundou and ESTZ samples are restricted by their occupational crosswalk, which covers 63 of the 81 NACE 2-digit divisions in the panel. Panel C varies what the rank is built from: a fully pre-pandemic 2019-only sales rank, an employment rank measuring input scale rather than product-market standing, and the baseline rank with six simultaneous pre-shock decile $\times$ country $\times$ quarter fixed-effect batteries (size, baseline PD, leverage, cash, profitability, and age). All specifications include firm $\times$ bank pair and bank $\times$ market $\times$ quarter fixed effects, bank-firm controls, and firm-level controls. t -statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

<i>Panel A: alternative exposure measures, top-quartile indicators (Incumbency rank $\times$ Exposure $\times$ Attention)</i>													
	AIIE-LM		AIIE-broad		Calvino		Eloundou		ESTZ				
	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)			
Incumbency rank $\times$ Exposure $\times$ Attention	0.074** (2.41)	0.075** (2.29)	0.061** (2.04)	0.061** (2.22)	0.044 (1.46)	0.052** (2.57)	0.053* (1.91)	0.052** (2.42)	0.041 (1.20)	0.043* (1.70)			
N	5,906,989	5,906,989	5,906,989	5,906,989	5,378,512	5,378,512	5,132,896	5,132,896	5,132,896	5,132,896			
R^2	0.745	0.745	0.745	0.745	0.743	0.743	0.743	0.743	0.743	0.743			
Memo: AIIE-LM triple, this sample	—	—	0.074** (2.41)	0.075** (2.29)	0.088** (2.54)	0.089** (2.35)	0.041 (1.39)	0.041* (1.82)	0.041 (1.39)	0.041* (1.82)			

continued on next page

Table A.8, continued

Panel B: the same measures entered continuously ($\text{Incumbency rank} \times z(\text{Exposure}) \times \text{Attention}$, per SD of exposure)											
	AII-E-LM		AII-E-broad		Calvino		Eloundou		ESTZ		
	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki	Google	Wiki	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Incumbency rank $\times z(\text{Exposure}) \times \text{Attention}$											
	0.015*	0.016	0.020**	0.020**	0.017**	0.017**	0.023**	0.024**	0.017**	0.018**	
	(1.75)	(1.61)	(2.19)	(2.05)	(2.00)	(2.12)	(2.39)	(2.23)	(2.11)	(2.15)	
N	5,906,989	5,906,989	5,906,989	5,906,989	5,378,512	5,378,512	5,132,896	5,132,896	5,132,896	5,132,896	
R^2	0.745	0.745	0.745	0.745	0.743	0.743	0.743	0.743	0.743	0.743	

Panel C: what the ranking is built on, and the kitchen sink ($\text{Incumbency rank} \times \text{High AI} \times \text{Attention}$)

	Output-market standing (2019-only sales rank)		Input scale (employment rank)		Baseline rank + kitchen sink	
	Google	Wiki	Google	Wiki	Google	Wiki
	(1)	(2)	(3)	(4)	(5)	(6)
Incumbency rank $\times \text{High AI} \times \text{Attention}$						
	0.071**	0.071**	0.035	0.031	0.076***	0.078***
	(2.56)	(2.24)	(1.31)	(1.28)	(3.70)	(4.41)
N	5,176,169	5,176,169	4,499,379	4,499,379	5,287,313	5,287,313
Six decile $\times \text{Ctry} \times \text{Qtr}$ batteries	N	N	N	N	Y	Y
R^2	0.742	0.742	0.735	0.735	0.744	0.744

Table A.9: Total effects by pre-shock market position

This table asks whether the average reassessment of Table 2 is concentrated among low-ranked firms, by estimating *High AI exposure* $\times$ *AI attention* separately for firms in the bottom and top halves of their market's pre-shock incumbency-rank distribution (Table 6). Regressions are estimated on the ranked sample in the baseline design, with firm and bank $\times$ country $\times$ quarter fixed effects, bank–firm controls, and Orbis fundamentals; the dependent variable is $\ln(PD)$ in columns 1–4 and the portfolio PD rank in columns 5–8. The bottom half contains 13% of ranked credit observations. t -statistics (standard errors double-clustered by firm and bank) are in parentheses; *, **, and *** denote significance at 10%, 5%, and 1%. Detailed variable definitions are in Table A.2.

	$\ln(PD)$				Portfolio PD rank			
	Bottom half		Top half		Bottom half		Top half	
	Google (1)	Wiki (2)	Google (3)	Wiki (4)	Google (5)	Wiki (6)	Google (7)	Wiki (8)
High AI exposure $\times$ AI attention	−0.089* (−1.82)	−0.075 (−1.65)	−0.067* (−1.80)	−0.060* (−1.76)	−0.011*** (−2.88)	−0.009*** (−3.01)	−0.013*** (−4.10)	−0.011*** (−3.97)
N	491,775	491,775	3,399,720	3,399,720	491,771	491,771	3,396,011	3,396,011
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank $\times$ Country $\times$ Qtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank–firm and Orbis controls	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.651	0.651	0.569	0.569	0.632	0.632	0.566	0.566

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