Who Benefits When Banks Go Digital? FinTech Adoption and SME Lending in the UK*

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Abstract

FinTech is reshaping traditional financial services including small and medium-sized enterprise (SME) credit. This paper investigates whether FinTech adoption by UK banks "democratises" SME credit, with a focus on underserved markets and risk implications. We develop a theoretical model of bank lending in which FinTech can affect credit supply through two distinct channels: reducing the cost of serving geographically remote borrowers and improving the precision of borrower screening. The model generates testable predictions that allow us to empirically distinguish between these mechanisms. Using a measure of FinTech adoption based on bank–FinTech business relationships and granular loan-level data, we find that FinTech adoption enables banks to extend larger, more affordable unsecured loans to SMEs, with benefits concentrated among low-risk, digitally assessable borrowers. The effects are strongest in rural regions, consistent with the model's prediction that FinTech drives geographic inclusion by reducing the marginal cost of reaching underserved borrowers without physical branch infrastructure, rather than through improved information processing.

Keywords: financial technology (FinTech), SME lending, bank-FinTech partnerships, credit access, geographic inclusion. **JEL Classification:** G21, G23, O33.

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1 Introduction

Financial technology (FinTech) is reshaping traditional financial services delivery and demonstrates considerable potential to address longstanding barriers to credit access. In recent years, there has been growing interest in understanding how FinTech affects credit access for small and medium-sized enterprises (SMEs), which traditionally face significant financing constraints due to limited collateral, lack of audited financial statements, or the absence of established banking relationships (Berger and Udell, 2006). While much of the literature focuses on non-bank FinTech lenders (Jagtiani and Lemieux, 2019; Gambacorta et al., 2023; Cornelli et al., 2024), an important but less studied phenomenon is the adoption of FinTech innovations by traditional banks, which often partner with FinTech companies given their limited ability to innovate internally (Hornuf et al., 2021). This study examines the impact of such partnerships on UK banks' lending to SMEs. Specifically, we investigate whether bank–FinTech partnerships enable traditional lenders to address longstanding market failures in SME finance, whether the benefits extend to underserved regions, and whether they come at the cost of higher credit risk.

The inadequacy of SME finance in the UK has been a persistent concern for nearly a century.[1] Despite the recent growth of alternative finance providers, UK SMEs remain heavily dependent on traditional bank lending (BEIS, 2020), with the five largest banks still accounting for approximately 40% of gross lending to SMEs (British Business Bank, 2024). This continued reliance leaves SMEs particularly vulnerable to tightening credit conditions and explains why supply-side constraints in bank lending have such significant macroeconomic consequences (Chodorow-Reich, 2014; Bentolila et al., 2018). Persistent geographic inequalities compound these challenges: SMEs in peripheral UK regions face greater difficulty accessing finance and are more likely to have loan applications rejected, becoming "discouraged borrowers" (Lee and Brown, 2017). There is also evidence of a "peripheral region price penalty", where banks al-

[1]The Macmillan Committee first identified a significant financing gap in 1931 (Macmillan, 1931). This gave rise to the enduring concept of the "Macmillan Gap", which subsequent government inquiries have repeatedly confirmed rather than resolved. The Bolton Committee (Bolton, 1971) and Wilson Committee (Wilson, 1979) both revisited these concerns in the 1970s, while the post-financial crisis Breedon Review estimated an aggregate SME finance gap of upwards of £84 billion (Breedon, 2012).

locate and price credit differently based on an SME's location (Cowling et al., 2019). The persistence of geographic frictions for SMEs is underscored by Core and De Marco (2024), who show that even when government guarantees eliminated screening incentives and loan applications were filed online, small business lending in Italy remained overwhelmingly local, with 90% of guaranteed loans issued within 10km of a bank branch. Against this backdrop, understanding whether FinTech can help address these market failures is of first-order importance for policy.

It is a priori unclear whether findings from the literature on non-bank FinTech lenders generalise to traditional banks adopting FinTech. Banks operate under fundamentally different institutional constraints: they face strict regulatory capital requirements and prudential supervision that may limit their ability or willingness to expand lending, even when adopting similar technologies. Buchak et al. (2018) show that regulatory differences between traditional banks and non-depository lenders accounted for roughly 60% of shadow bank growth in US mortgage origination, underscoring how the regulatory environment—rather than technology alone—shapes lending outcomes. From a methodological perspective, studying regulated banks provides a key advantage: it allows us to isolate the effect of technology adoption itself, holding constant the regulatory environment.

A central challenge in this literature is distinguishing between the channels through which FinTech affects lending outcomes. Prior work has identified two broad mechanisms. The first is a *cost-reduction channel*: digital screening lowers the per-borrower cost of assessing and serving SMEs, particularly those far from bank branches, thereby shifting the credit supply curve outward. The second is an *information-precision channel*: FinTech improves the quality of screening signals, enabling banks to lend to borrowers they previously could not assess. These channels have fundamentally different implications for *who* benefits. The precision channel predicts that FinTech helps banks lend to opaque borrowers they previously could not screen; the cost channel predicts that FinTech helps banks lend more cheaply to transparent borrowers they could already assess. Yet, existing empirical work typically estimates reduced-form effects

without a theoretical framework to separate the two.

To address this identification challenge, we develop a theoretical model that nests both channels in a unified framework and derives sharply contrasting predictions. Our model incorporates distance-dependent screening costs and signal precision. Screening technology is borrower-type-dependent: low-risk ("transparent") borrowers can be assessed digitally at low cost, while high-risk ("opaque") borrowers require costly relationship-based screening regardless of the bank's FinTech capability. This distinction follows the formal separation between codifiable hard information and relationship-based soft information in Berger and Udell (2002); Liberti and Petersen (2019). The two channels generate a set of *differential diagnostic tests* across borrower risk type, geographic remoteness, and their interaction. Under the cost-reduction channel, FinTech benefits accrue exclusively to low-risk borrowers, effects are amplified by distance, and the triple interaction of FinTech intensity $\times$ low-risk status $\times$ remoteness is positive and significant. Under the information-precision channel, effects extend to high-risk borrowers, geographic amplification is symmetric across risk types, and the triple interaction is approximately zero.

Guided by these predictions, our empirical analysis provides several novel insights. First, we find that FinTech enables banks to extend larger and more affordable unsecured loans: on average, a one-unit increase in FinTech intensity increases loan volumes by 6.33% and reduces interest rate spreads by 9.18 basis points. Second, consistent with Diagnostic Test 1, these effects are highly heterogeneous: the benefits accrue exclusively to low-risk borrowers, with no evidence of similar effects for subprime firms—the pattern predicted by the cost-reduction channel and inconsistent with the information-precision channel. Third, consistent with Diagnostic Tests 2 and 3, we find larger effects in underserved regions—loan volumes increase by 9.5–11.4% in remote, low population-density areas compared to 5.6–6% in urban centres—but this geographic amplification applies only to low-risk borrowers. The significant triple interaction and the absence of geographic effects for high-risk firms collectively point to cost reduction as the dominant mechanism. Finally, we exploit variation in branch closures across

UK regions to show that FinTech-adopting banks can maintain SME lending despite reduced physical presence—a finding that further corroborates the cost-reduction interpretation, since it is physical infrastructure costs that FinTech most directly displaces. This mechanism is particularly salient in the UK, where branch networks have contracted sharply, with closures concentrated in peripheral regions already facing credit constraints.

Our results are policy relevant. They suggest that (i) FinTech adoption can help address the SME financing gap—a longstanding market failure in the UK; (ii) FinTech acts as an "equaliser" and disproportionately benefits underserved regions; (iii) FinTech achieves these benefits without leading to higher risk-taking by banks, as the effects are concentrated among low-risk borrowers. However, the findings also reveal important limitations. The benefits do not extend to higher-risk SME borrowers, who likely face the most severe financing constraints. Our model clarifies why: these borrowers require relationship-based screening that does not scale digitally, and the cost-reduction channel—which drives the aggregate effects—operates only for borrowers whose creditworthiness can be assessed through automated means.

The remainder of the paper proceeds as follows. Section 2 reviews the literature. Section 3 presents the theoretical framework. Section 4 describes our data sources and how we measure FinTech adoption at the bank level. Section 5 presents our empirical methodology and results. Section 6 concludes.

2 Related literature

FinTech is reshaping traditional financial services. The literature has identified two broad channels through which FinTech may affect lending—improving the precision of borrower screening and reducing the cost of loan origination and servicing. We organise this section around these channels, noting that many empirical findings are consistent with both mechanisms operating simultaneously—an ambiguity that motivates the diagnostic framework we develop in Section 3. Much of this empirical evidence comes from studies of non-bank FinTech lenders, which ex-

panded as banks retrenched under tighter oversight (Buchak et al., 2018). We then discuss the emerging literature on bank–FinTech partnerships.

2.1 The information-precision channel

A first strand of the literature emphasises that FinTech improves the accuracy with which lenders screen borrowers, easing the information asymmetries that constrain SME finance. The clearest empirical evidence for this channel comes from studies that directly measure improvements in screening accuracy. Alternative data and machine learning enable FinTech lenders to identify creditworthy but opaque borrowers who lack traditional credit records (Jagtiani and Lemieux, 2019). Machine learning-based credit scoring models using non-traditional data demonstrate superior predictive power, particularly following adverse shocks (Gambacorta et al., 2024). Cornelli et al. (2024) show that FinTech platforms' internal credit scores, which incorporate alternative data through ML models, outperform traditional FICO and VantageScores in predicting small business loan defaults, with the informational advantage particularly pronounced in economically underserved areas. Even simple digital footprint variables—passive traces left by users accessing websites—can match or exceed the predictive power of credit bureau scores and help assess previously unscorable borrowers (Berg et al., 2020). In the consumer credit context, Jagtiani et al. (2025) demonstrate that FinTech partnerships enable banks to price nonprime mortgage loans more accurately, charging lower risk premiums to creditworthy nonprime borrowers while maintaining appropriate premiums for genuinely risky ones. Not all evidence supports improved screening, however: Beaumont et al. (2021) find no evidence of superior screening ability by FinTech platforms—FinTech borrowers are in fact more likely to default ex post—suggesting that the growth of FinTech SME lending in their setting is driven by product differentiation (uncollateralised credit) rather than improved information processing.

A key question is whether the informational gains from FinTech stem primarily from better algorithms or richer data. Chen et al. (2025) provide rare direct evidence by exploiting a Chi-

nese bank's phased technology adoption. They show that AI and big data adoption jointly produce large improvements in credit rating accuracy and significant reductions in default rates for SMEs, and that the combination narrows borrowing cost disparities between small and large firms. Crucially, however, the gains are asymmetric across the two components: an initial upgrade to machine learning models alone yielded only modest improvements in rating accuracy and no significant reduction in defaults, whereas the subsequent integration of big data analytics—incorporating real-time transaction data, VAT invoices, and unstructured text—more than doubled the gains in accuracy and drove the entire default reduction. This finding resonates with evidence from big tech lending, where the informational advantage derives less from algorithmic sophistication than from the data environment itself. Gambacorta et al. (2023) show that BigTech lenders can substitute traditional safeguards such as collateral and relationship banking with ecosystem-based, real-time cash-flow observation and automated repayment, leveraging their platform integration to monitor borrowers continuously. Taken together, these studies suggest that the information-precision channel operates primarily through the richness of data inputs, and that the full potential of AI in credit assessment is realised only when paired with comprehensive alternative data—an advantage that BigTech platforms possess structurally but that traditional banks must acquire through partnerships or investment.

2.2 The cost-reduction channel

A second strand suggests that FinTech lowers the cost of originating and servicing loans. Transaction cost theory predicts that digitisation lowers persistently high intermediation costs (Philippon, 2016). Petersen and Rajan (2002) document that average borrower–lender distances increased substantially as banks adopted information technology, arguing that technology increases the availability of hard information that can substitute for proximity-based screening, rather than making soft information easier to collect at a distance. Fuster et al. (2019) document that end-to-end automation speeds up mortgage processing by 20%. Intensified FinTech competition can also discipline incumbent banks to invest in technology: He et al. (2022) show that following the entry of Lending Club, commercial banks significantly increased their soft-

ware IT spending—investment specifically in hard-information processing—consistent with a competitive "catching-up" response.

Survey evidence on bank–FinTech partnerships further supports the cost-reduction interpretation. Klus et al. (2019) find that banks' dominant motive for partnering with FinTech firms is outsourcing rather than learning: banks view these alliances primarily as operational efficiency tools—accessing digital solutions at lower cost and circumventing slow internal development—rather than as vehicles for transforming their internal information-processing capabilities. This suggests that, at least from banks' own perspective, the expected gains from FinTech partnerships operate primarily through the cost channel.

The potential gains from cost reduction depend on the magnitude of the underlying frictions. Amiti et al. (2026) quantify these directly, using confidential U.S. supervisory data on over 160,000 commercial loans to show that observable risk characteristics explain only about a quarter of loan spread variation among similar borrowers. They attribute the residual dispersion to search costs—the costs of filing applications and providing information for screening—and estimate that roughly 37 percent of borrowers accept the first quote they receive. Crucially, estimated search costs are highest for riskier, more opaque, and smaller borrowers, providing a direct measure of the per-borrower frictions that FinTech digitisation could compress.

It is worth noting that direct evidence on cost reduction is inherently harder to obtain than evidence on screening accuracy. Improvements in signal quality can be measured through default prediction, credit score comparisons, or ex-post loan performance—outcomes that are readily observable in standard datasets. By contrast, reductions in per-borrower screening or origination costs are typically unobserved by the econometrician, manifesting only indirectly through expanded lending volumes, lower spreads, or greater geographic reach—outcomes that are equally consistent with improved information precision. This asymmetry in observability may partly explain why the empirical literature leans toward the precision interpretation even when the underlying effects could reflect cost reduction, and it underscores the need for the

diagnostic framework we develop in Section 3.

2.3 Evidence consistent with both channels

Several important studies document effects of technology on lending outcomes—particularly geographic expansion, pricing, and default reduction—that are consistent with both channels operating simultaneously, without isolating which mechanism dominates.

Piao et al. (2024) show that AI enables banks to extend credit to distant borrowers and that higher AI use weakens the distance–lending gradient, with AI-adopting banks shifting credit toward poorer, bank-scarce areas. They interpret this as AI improving the collection and analysis of hard information. However, the same pattern would arise if AI reduced the marginal cost of serving remote borrowers, since both mechanisms predict that technology flattens the distance–lending gradient. Core and De Marco (2024) show that banks with better IT provide more, faster, and cheaper guaranteed loans to small businesses and can lend in areas where they lack branches. The speed and pricing effects point toward cost reduction, while lending without branch presence could reflect either improved remote screening or lower distance-related costs. Similarly, D'Andrea et al. (2025) find that broadband-connected branches originate more loans outside their home province—including to borrowers without prior credit history—and that broadband access delivers modest pricing declines. The expansion to borrowers without credit history suggests informational gains, while the pricing effects and geographic reach are equally consistent with cost reduction. Pierri and Timmer (2022) show that banks with greater IT adoption experienced smaller increases in non-performing loans during the global financial crisis, which could reflect either superior screening or more efficient loan management. More broadly, FinTech presence expands inclusion in highly concentrated banking markets and areas experiencing branch declines (Jagtiani and Lemieux, 2017). Kutzbach and Pogach (2024) show that financial technology facilitated banks' out-of-area lending of government-backed PPP loans during COVID-19, where technology substituted for physical proximity—again consistent with either channel.

The difficulty of disentangling these mechanisms in reduced-form empirical work is a central motivation for the theoretical framework we develop in Section 3. Our model generates diagnostic predictions—based on the interaction of FinTech intensity with borrower risk type and geographic distance—that allow the data to distinguish between channels even when both may be active.

2.4 Our contribution

We build on this emerging literature by providing the first comprehensive evidence on bank-adopted FinTech's impact on SME lending. Our contribution is threefold. First, we develop a unified theoretical framework that nests both the cost-reduction and information-precision channels, generating sharply contrasting predictions that allow us to distinguish between mechanisms empirically. As the preceding discussion makes clear, most existing studies estimate reduced-form effects of technology adoption without a framework to separate the two channels—yet the distinction matters fundamentally for understanding *who* benefits from FinTech. The model incorporates distance-dependent screening costs and borrower-type-dependent screening technology, so that digital assessment effectiveness depends on borrower opacity. We assume that FinTech is more effective at screening borrowers whose creditworthiness can be assessed through hard, codifiable information, and that these borrowers tend to be low-risk. This assumption is central to the model's predictions. The distinction between codifiable hard information and relationship-based soft information that underpins this heterogeneity follows Berger and Udell (2002); Liberti and Petersen (2019), and is discussed by Vives (2019) in a broader review of digital disruption in banking. Our modelling choice is consistent with the literature pointing to the fact that FinTech advantages are in processing hard information rather than "hardening" soft information (Balyuk et al., 2025; Fuster et al., 2019; He et al., 2022). We endogenise loan size using the variable-investment moral hazard framework of Holmström and Tirole (1997), and derive diagnostic predictions across borrower risk, geography, and their interaction.

Second, we implement all three diagnostic tests derived from the model, exploiting heterogeneity across borrower risk type, geographic remoteness, and their interaction. Third, by studying regulated banks, we isolate the effect of technology adoption holding constant the regulatory environment—an advantage over comparisons between non-bank FinTech lenders and traditional banks, which confound technology with regulatory differences.

3 Theoretical framework

We develop a model of bank lending to SMEs that nests two channels through which fintech affects credit markets: a cost-reduction channel, in which digital screening lowers the cost of assessing transparent borrowers independently of distance, and an information-precision channel, in which fintech improves the quality of screening signals for all borrowers. The two channels generate distinct predictions across borrower risk type and geography, enabling us to distinguish between them empirically. The cost-reduction channel predicts effects concentrated among low-risk borrowers with geographic amplification; the information-precision channel predicts effects for all borrowers, concentrated among the previously hardest-to-screen.

3.1 Borrowers and moral hazard

A continuum of risk-neutral SMEs (entrepreneurs) are distributed across geographic space. Each entrepreneur i is characterized by its location, with $d_i \geq 0$ capturing its distance from the nearest bank branch, and its type $\theta_i \in \{L, H\}$, which is unobservable without screening. Low-risk borrowers ($\theta = L$) have a probability of project success p_L (high), while high-risk ones ($\theta = H$) have a probability of project success p_H (low), with $p_H < p_L$.

Each entrepreneur has initial wealth $A > 0$ and access to an investment project with

variable scale. A project of scale I (total investment) yields:

$$\tilde{R} = \begin{cases} R \cdot I & \text{with probability } p_\theta \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $R > 0$ is the return per unit of investment and p_θ is the type-dependent probability of success conditional on high effort. The entrepreneur borrows $I - A$ from a bank.

The entrepreneur faces a classical moral hazard problem (see, e.g. Holmström and Tirole (1997), Tirole (2006), Ch.3). After receiving the loan, she chooses either high or low effort. If she chooses high effort, the probability of success is p_θ and she derives no private benefit. If she chooses low effort, the probability of success is only $p_\theta - \Delta p$, but she earns private benefit $B \cdot I$. The private benefit parameter $B > 0$ and the effort wedge $\Delta p > 0$ are the same for both borrower types. The key heterogeneity across types is in the base success probability p_θ.

3.2 Banks and screening technology

A competitive banking sector has access to funds at opportunity cost normalised to 1 (the risk-free rate is zero). The bank must screen each borrower to assess type θ before lending.

Assumption 1 (Positive NPV)**.** *Both project types have positive NPV under high effort:* $p_\theta R > 1$ *for* $\theta \in \{L, H\}$.

Assumption 2 (Binding moral hazard)**.** *Moral hazard constrains financing:* $p_\theta \left(R - \frac{B}{\Delta p}\right) < 1$ *for* $\theta \in \{L, H\}$.

Assumption 2 ensures that moral hazard creates a genuine financing friction. As shown in Section 3.3, the incentive compatibility constraint requires the entrepreneur to retain a minimum stake $B/\Delta p$ per unit of investment to discourage shirking. The maximum expected return per unit of investment that can be pledged to the lender—the *pledgeable income*—is therefore $p_\theta(R - B/\Delta p)$. Assumption 2 requires this to fall short of the unit cost of investment for both borrower types, so that no borrower can be fully financed from pledgeable income alone.

Entrepreneurs must therefore contribute their own wealth A to bridge the gap, and the extent to which internal funds can be leveraged into investment—the equity multiplier $1/(1-\mathcal{P}_\theta)$ derived in equation (18)—becomes the key margin through which screening costs and signal precision affect loan size. Combined with Assumption 1, this defines a standard credit-rationing environment: projects are socially valuable but cannot be fully externally financed, making the bank's screening technology and cost structure economically consequential.

Relationship screening Without fintech, the bank screens all borrowers using traditional relationship lending where "soft information" is acquired by loan officers through site visits, management interviews, and local information gathering (see Berger and Udell, 2002; Liberti and Petersen, 2019; Boot and Thakor, 2000, on the role of soft information). The per-loan screening cost is:

$$c^{Rel}(d) = c_0 + \gamma \cdot d \tag{2}$$

where $c_0 > 0$ is the fixed component and $\gamma > 0$ captures the marginal cost of distance. The screening signal under relationship lending has precision $\alpha^{Rel}(d) \in (0,1)$, where α denotes the probability that the signal correctly reveals the borrower's type.[2] Under traditional lending, precision declines with distance:

$$\alpha^{Rel}(d) = \bar{\alpha} - \beta d \tag{3}$$

where $\bar{\alpha} \leq 1$ is precision at $d = 0$ and $\beta > 0$ captures the erosion of information quality with distance[3]

Fintech The bank's fintech intensity $\phi \in [0,1]$ parameterises the extent to which digital screening infrastructure has been deployed. Fintech potentially operates through two channels, cost reduction and information precision.

Channel 1: Cost reduction. With probability ϕ, the bank can process a loan application

[2] A precision of $\alpha = 1$ denotes a perfectly informative signal; $\alpha = 0$ is uninformative.

[3] See Hauswald and Marquez (2006) for a similar assumption in a different model and see Agarwal and Hauswald (2010) for empirical evidence that borrower proximity enhances the quality of collected soft information.

through digital screening rather than relationship screening. Digital screening costs:

$$c^{Dig} = c_D, \quad \text{with } c_D < c_0 \tag{4}$$

with no distance dependence. However, digital screening is type-dependent in its effectiveness:

- For **low-risk borrowers** ($\theta = L$): Digital screening works and produces a signal with precision $\alpha_L^{Dig} = 1$. These borrowers are *transparent*—their creditworthiness can be assessed through hard, quantifiable data.
- For **high-risk borrowers** ($\theta = H$): Digital screening is uninformative ($\alpha_H^{Dig} = 0$). These borrowers are *opaque*—their assessment requires soft information that cannot be digitised but rather has to be collected through relationship lending. Accordingly, we assume that when digital screening fails (for high-risk borrowers), the bank must fall back on relationship screening, incurring cost $c^{Rel}(d)$.

The distinction in the effectiveness of FinTech for screening different borrower types is central to the model's predictions.[4] This modelling choice builds on the framework of Liberti and Petersen (2019), who emphasise that hard information (quantitative, context-independent data) can be collected, stored, and transmitted at scale without loss of meaning, because its interpretation does not depend on the context of its collection. As they document, these properties underpin the expansion of technology-driven lending, since production technologies that rely on hard information are easier to automate and benefit from economies of scale, enabling credit decisions to be separated from the personal collection of information. This distinction is also consistent with the early evidence in Petersen and Rajan (2002), who argue that information technology does not make soft information easier to collect at a distance, but instead increases the availability of hard information that can substitute for proximity-based screening. The assumption is also in line with Balyuk et al. (2025), who find that FinTech credit more often substitutes for loans by large banks rather than small banks. Their finding is consistent with FinTech advan-

[4]The assumption of a perfect signal for low-risk borrowers and an uninformative signal for high-risk borrowers is made for tractability. It can be relaxed to allow intermediate precision levels without altering the qualitative predictions.

tages in processing hard information rather than "hardening" soft information. Fuster et al. (2019) document that FinTech mortgage lenders rely on a less personalised loan process centred on hard information, and note that this approach may reduce credit to applicants whose assessment requires soft information gathered through face-to-face interactions. Finally, He et al. (2022) show that when incumbent banks respond to FinTech entry, they increase investment specifically in software IT—which facilitates hard-information processing—rather than in communication IT, which supports soft-information production and transmission. This asymmetric investment response suggests that banks themselves treat FinTech as a hard-information technology, consistent with the type-dependent screening we model.

Channel 2: Information precision. FinTech may also improve the precision of screening signals for *all* borrowers by enhancing the bank's information-processing capabilities. Under this channel, fintech intensity ϕ augments the precision of the relationship screening signal:

$$\alpha^{Rel}(d, \phi) = \bar{\alpha} + \lambda\phi - \beta d \tag{5}$$

where $\lambda \geq 0$ parameterises the strength of the information-precision channel. When $\lambda = 0$, fintech operates purely through cost reduction; when $\lambda > 0$, it also improves signal quality. The precision improvement applies equally to both borrower types, since it operates through enhanced data analytics applied to the relationship screening process itself (e.g., better algorithms for processing loan officer reports, or natural language processing of management interviews).

Combining both channels, the expected screening cost for each borrower type is:

$$C_L(d, \phi) = \phi \cdot c_D + (1 - \phi)(c_0 + \gamma d) \tag{6}$$

$$C_H(d, \phi) = c_0 + \gamma d \tag{7}$$

The cost channel operates *only* through C_L: low-risk borrowers benefit from cheaper digital

screening, while high-risk borrowers always require full relationship screening.

The effective screening precision for each borrower type is:

$$\alpha_L^{eff}(d,\phi) = \phi \cdot 1 + (1-\phi)\left(\bar{\alpha} + \lambda\phi - \beta d\right) \tag{8}$$

$$\alpha_H^{eff}(d,\phi) = \phi \cdot 0 + (1-\phi)\left(\bar{\alpha} + \lambda\phi - \beta d\right) \tag{9}$$

When the digital channel is available (probability ϕ), low-risk borrowers receive a perfect signal while high-risk borrowers receive an uninformative one. In both cases, the relationship channel (probability $1-\phi$) has fintech-augmented signal precision. For high-risk borrowers, the digital channel is actually *harmful* to precision (it contributes 0 rather than the relationship-based $\bar{\alpha} + \lambda\phi - \beta d$), so the bank optimally ignores it and uses relationship screening regardless.[5] Hence, in practice:

$$\alpha_L^{eff}(d,\phi) = \phi + (1-\phi)\left(\bar{\alpha} + \lambda\phi - \beta d\right) \tag{10}$$

$$\alpha_H^{eff}(d,\phi) = \bar{\alpha} + \lambda\phi - \beta d \tag{11}$$

Table 1 summarises how each channel affects each borrower type.

Table 1: Channel structure

	Low-risk ($\theta = L$)	**High-risk** ($\theta = H$)
Cost-reduction channel	$\partial C_L/\partial\phi < 0$	$\partial C_H/\partial\phi = 0$
Information-precision channel	$\partial\alpha_L^{eff}/\partial\phi > 0$	$\partial\alpha_H^{eff}/\partial\phi = \lambda > 0$

The crucial asymmetry is that the cost channel is *type-specific* (affecting low-risk borrowers only), while the precision channel is *type-general* (affecting both types).

[5] Formally, for high-risk borrowers the bank strictly prefers to use relationship screening whenever $\bar{\alpha} + \lambda\phi - \beta d > 0$, which holds for d not too large. We assume this holds throughout.

3.3 Optimal lending contract

3.3.1 Incentive compatibility constraint

The entrepreneur receives $R_b \cdot I$ upon project success and zero otherwise. To ensure the entrepreneur exerts effort (choosing high effort over shirking), the expected gain from exerting high effort must weakly exceed the expected gain from shirking plus the private benefit:

$$p_\theta \cdot R_b \cdot I \geq (p_\theta - \Delta p) \cdot R_b \cdot I + B \cdot I \tag{12}$$

Dividing through by I and rearranging yields the incentive compatibility constraint:

$$R_b \geq \frac{B}{\Delta p} \tag{13}$$

where $\Delta p > 0$ denotes the reduction in success probability from shirking. This is a standard result (see Tirole (2006), Ch.3): the minimum incentive-compatible stake R_b is pinned down entirely by the moral hazard parameters $(B, \Delta p)$ and is independent of the borrower's type θ. Intuitively, the temptation to shirk—captured by the ratio of private benefit to the probability wedge—is identical across borrower types, so the per-unit-of-investment pledge needed to align incentives does not vary with p_θ. This invariance implies that type-dependent differences in pledgeable income, and hence in borrowing capacity, arise solely through the success probability p_θ rather than through the incentive constraint itself.

3.3.2 Incorporating signal precision

Signal precision affects lending through the bank's posterior belief about borrower type. Before screening, the bank knows only that a borrower is low-risk with prior probability μ and high-risk with probability $1-\mu$. A bank that receives a positive signal with precision α updates its belief about the probability that the borrower is truly the type indicated by the signal. Formally, let $\alpha_\theta^{eff} \in [0, 1]$ denote the effective signal precision for a type-θ borrower, where $\alpha_\theta^{eff} = 0$ corresponds to a completely uninformative signal and $\alpha_\theta^{eff} = 1$ to perfect type revelation. The

expected probability of project success, conditional on a positive screening signal with precision α_θ^{eff}, is:

$$\hat{p}_\theta(\alpha) = \alpha_\theta^{eff} \cdot p_\theta + (1 - \alpha_\theta^{eff}) \cdot \bar{p} \tag{14}$$

where $\bar{p} = \mu p_L + (1 - \mu) p_H$ is the prior expected success probability and μ is the population share of low-risk borrowers. Equation (14) can be interpreted as a precision-weighted average: with weight α_θ^{eff} the bank trusts the signal and assigns the type-specific success probability p_θ, while with the complementary weight $(1-\alpha_\theta^{eff})$ the bank falls back on the population prior $\bar{p}$.

When signals are perfect ($\alpha_\theta^{eff} = 1$), the bank knows the borrower's type with certainty and sets $\hat{p}_\theta = p_\theta$. The lender can then price each loan according to its true risk, fully differentiating between low- and high-risk borrowers. When signals are completely uninformative ($\alpha_\theta^{eff} = 0$), the posterior collapses to the prior: $\hat{p}_\theta = \bar{p}$ for all θ, and the bank cannot distinguish between types at all. In the empirically relevant interior case ($\alpha_\theta^{eff} \in (0, 1)$), the bank faces residual uncertainty about borrower quality. This uncertainty compresses the posterior toward $\bar{p}$, which has asymmetric consequences across types: for low-risk borrowers ($p_L > \bar{p}$), imprecise screening *understates* their true creditworthiness, reducing their perceived pledgeable income and tightening credit terms. For high-risk borrowers ($p_H < \bar{p}$), the same imprecision *overstates* their quality, generating an adverse selection subsidy.

This asymmetry is central to the model's predictions. Improvements in signal precision—whether through fintech adoption or other technological advances—benefit low-risk borrowers disproportionately by moving $\hat{p}_L$ closer to its true (higher) value p_L, while simultaneously correcting the overestimation of high-risk borrowers. As we show below, this mechanism generates testable predictions about the heterogeneous effects of fintech across borrower risk profiles that are distinct from those produced by the cost-reduction channel alone.

3.3.3 Pledgeable income and loan size

Under the optimal contract, the entrepreneur retains the minimum incentive-compatible stake $R_b = B/\Delta p$ per unit of investment, and the lender receives the residual $R - B/\Delta p$ upon project success. The maximum expected repayment per unit of investment that the bank can extract while preserving the entrepreneur's incentive to exert effort—the *pledgeable income*—is therefore:

$$\mathcal{P}_\theta(\alpha) \equiv \hat{p}_\theta(\alpha) \left(R - \frac{B}{\Delta p} \right) \tag{15}$$

Pledgeable income is the product of two components: the bank's posterior belief about the probability of success, $\hat{p}_\theta(\alpha)$, and the per-unit surplus that can be pledged to the lender, $R - B/\Delta p$. The second term is type-independent (as established in Section 3.3), so all type-dependence in pledgeable income flows through the posterior $\hat{p}_\theta$. Since $p_L > p_H$, and since higher true success probability maps into a higher posterior for any given signal precision, we have $\mathcal{P}_L > \mathcal{P}_H$: low-risk borrowers can pledge more expected income per unit of investment, and hence can support more external financing.

Higher signal precision increases pledgeable income by raising $\hat{p}_\theta$. As precision improves, the bank becomes more confident that the borrower is the type indicated by the signal: for a borrower screened as low-risk, the posterior $\hat{p}_L$ moves closer to p_L, increasing the expected repayment the bank can count on. This raises the amount the bank is willing to lend per unit of the entrepreneur's own capital.

Optimal loan size. Under competitive lending, the bank earns zero expected profit. The bank's break-even condition requires that the expected repayment from the loan covers the total cost of funds plus screening:

$$\hat{p}_\theta(\alpha) \left(R - \frac{B}{\Delta p} \right) I = I - A + C_\theta(d, \phi) \tag{16}$$

The left-hand side is the bank's expected income: the pledgeable income per unit of investment, $\mathcal{P}_\theta$, times total investment scale I. The right-hand side is the bank's total outlay: the loan

amount $I-A$ (total investment minus the entrepreneur's equity contribution) plus the screening cost $C_\theta(d,\phi)$. Rearranging for I:

$$\mathcal{P}_\theta \cdot I = I - A + C_\theta \qquad \Longrightarrow \qquad I(1-\mathcal{P}_\theta) = A - C_\theta \tag{17}$$

which yields the maximum feasible investment scale:

$$I^*_\theta(d,\phi) = \frac{A - C_\theta(d,\phi)}{1 - \mathcal{P}_\theta\Big(\alpha^{eff}_\theta(d,\phi)\Big)} \tag{18}$$

This expression has a natural interpretation as an equity multiplier. The numerator, $A - C_\theta$, is the entrepreneur's *effective equity*: her initial wealth net of the screening cost that must be borne before lending can proceed. The denominator, $1 - \mathcal{P}_\theta$, captures the *financing gap* per unit of investment—the fraction of each invested pound that cannot be covered by pledgeable income and must therefore be financed by the entrepreneur's own funds. The ratio of the two gives the total investment that can be supported: each pound of effective equity is leveraged by the multiplier $1/(1-\mathcal{P}_\theta)$. When pledgeable income is high (i.e., $\mathcal{P}_\theta$ is close to 1), the financing gap is small and each pound of equity supports a large total investment. When pledgeable income is low, the multiplier shrinks and the entrepreneur is more severely credit-rationed.

Equation (18) is the key equation of the model. It reveals that fintech affects loan size through two channels simultaneously, each operating on a different component of the expression:

1. **Cost channel** (numerator): reducing screening costs C_θ increases effective equity $A-C_\theta$, directly expanding the base of capital that can be leveraged. This channel operates only for low-risk borrowers, since high-risk borrowers always require relationship screening at cost $C_H = c_0 + \gamma d$ regardless of fintech intensity.

2. **Information channel** (denominator): increasing signal precision α^{eff}_θ raises the posterior $\hat{p}_\theta$ and hence pledgeable income $\mathcal{P}_\theta$, which increases the equity multiplier $1/(1-\mathcal{P}_\theta)$.

This channel operates for both borrower types, since improved screening signals allow the bank to price loans more accurately for any borrower.

Crucially, the two channels are *complementary*: a simultaneous reduction in screening cost and improvement in signal precision generates a larger increase in loan size than either channel alone, because higher effective equity is amplified by a larger multiplier. This complementarity is especially pronounced for low-risk borrowers in remote areas, who benefit from both channels simultaneously.

3.3.4 Interest rate spread

The interest rate spread measures the premium above the risk-free rate that the borrower pays on her loan. Under competitive lending with zero expected profits, this spread must be just sufficient to cover the bank's screening cost and the expected loss from default. To derive the spread, note that the bank charges a gross interest rate r_θ on the loan amount $I - A$. The bank's zero-profit condition requires that expected repayment equals the loan disbursement plus screening cost:

$$\hat{p}_\theta(\alpha) \cdot r_\theta \cdot (I - A) = (I - A) + C_\theta(d, \phi) \tag{19}$$

The left-hand side is the bank's expected revenue: with probability $\hat{p}_\theta$ the project succeeds and the bank receives repayment $r_\theta \cdot (I - A)$; with the complementary probability the project fails and the bank receives nothing. The right-hand side is the bank's total outlay. Solving for the gross interest rate:

$$r_\theta = \frac{1}{\hat{p}_\theta} + \frac{C_\theta}{\hat{p}_\theta \cdot (I - A)} \tag{20}$$

The spread above the risk-free rate (normalised to zero) is $s_\theta = r_\theta - 1$. Expressing the spread per unit of total investment rather than per unit of borrowing, and substituting the optimal loan size from equation (18), the equilibrium spread under competitive lending is:

$$s_\theta(d, \phi) = \frac{C_\theta(d, \phi)}{\hat{p}_\theta\left(\alpha_\theta^{eff}\right) \cdot I_\theta^*(d, \phi)} \tag{21}$$

The spread has an intuitive structure. The numerator is the total screening cost $C_\theta(d, \phi)$, which must be recovered through the interest margin. The denominator is the expected loan revenue base: the posterior probability of success $\hat{p}_\theta$ times the total investment scale I^*_θ. Because the bank can only recover screening costs when the project succeeds, the cost must be spread over the expected—rather than the actual—repayment, inflating the required margin by the inverse of $\hat{p}_\theta$.

Fintech reduces spreads through the same two channels that increase loan size, but with an important difference—both channels now operate through the denominator as well as the numerator:

1. **Cost channel**: A reduction in C_θ directly lowers the numerator—there is simply less cost to recover. Simultaneously, the resulting increase in I^*_θ expands the denominator, further diluting the per-unit cost burden. Both effects push spreads down, but only for low-risk borrowers.

2. **Precision channel**: An improvement in α^{eff}_θ raises $\hat{p}_\theta$, which increases the denominator through two mechanisms: directly (the expected repayment probability rises) and indirectly (higher pledgeable income raises I^*_θ via the equity multiplier). For both borrower types, the bank expects to be repaid more frequently and on a larger loan, so the screening cost can be amortised over a larger expected revenue base.

The spread expression also reveals a scale economy in screening: because C_θ is a fixed per-loan cost while I^*_θ is endogenous, any mechanism that increases loan size—whether through lower costs or better signals—mechanically reduces the spread by spreading the fixed screening expense over a larger investment. This implies that the spread and loan-size effects of fintech are not independent predictions but are jointly determined by the same underlying forces.

3.4 Predictions under each channel

We now derive predictions under each channel separately, then characterise how the data can distinguish between them. For clarity, we present the *pure* cost-reduction channel ($\lambda = 0$) and the *pure* information-precision channel ($c_D = c_0$, $\gamma = 0$ for the digital channel, so cost effects are shut down) before discussing the nested model. All formal proofs are collected in Appendix A.

3.4.1 Pure cost-reduction channel ($\lambda = 0$)

We first consider the case in which fintech operates exclusively through cost reduction, with no effect on signal quality. Formally, we set $\lambda = 0$ in equation (5), so that the precision of relationship screening is $\alpha^{Rel}(d) = \bar{\alpha} - \beta d$ regardless of ϕ. Under this channel, fintech substitutes cheap, distance-independent digital screening (c_D) for expensive, distance-dependent relationship screening ($c_0 + \gamma d$). Crucially, this substitution is only effective for low-risk borrowers, whose creditworthiness can be assessed through hard data. High-risk borrowers remain opaque to digital tools and must always be screened through relationship lending. The predictions that follow therefore exhibit a sharp asymmetry across borrower types.

Prediction 1 (Cost channel: loan size)**.** *Under the cost-reduction channel:*

(a) $\partial I_L^*/\partial\phi > 0$*: fintech increases loan size for low-risk borrowers.*

(b) $\partial I_H^*/\partial\phi = 0$*: fintech has no effect on loan size for high-risk borrowers.*

The proof is given in Appendix A.1.

Prediction 2 (Cost channel: spreads)**.** *Under the cost-reduction channel:*

(a) $\partial s_L/\partial\phi < 0$*: fintech reduces spreads for low-risk borrowers.*

(b) $\partial s_H/\partial\phi = 0$*: fintech has no effect on spreads for high-risk borrowers.*

The spread result follows directly from the loan-size prediction combined with the spread expression in equation (21). For low-risk borrowers, fintech reduces the numerator of the spread (lower screening cost C_L) while simultaneously increasing the denominator (larger loan size I_L^*

and unchanged $\hat{p}_L$). Both forces compress the spread. For high-risk borrowers, neither the screening cost nor the loan size changes, so spreads are unaffected.

Prediction 3 (Cost channel: geographic amplification)**.** *Under the cost-reduction channel:*

(a) $\partial^2 I_L^*/\partial\phi\,\partial d > 0$*: fintech effects on loan size are amplified at greater distance for low-risk borrowers.*

(b) $\partial^2 I_H^*/\partial\phi\,\partial d = 0$*: there is no geographic amplification for high-risk borrowers.*

The proof is given in Appendix A.2.

The geographic amplification arises because digital screening eliminates the distance component of screening costs entirely, while relationship screening incurs a cost that grows linearly in d at rate γ. The cost saving from switching to digital screening is therefore $c_0 + \gamma d - c_D$, which is increasing in distance. A remote low-risk borrower (high d) saves more from digital screening than a nearby one (low d), because the distance-related cost that fintech eliminates is larger. Dividing by the equity multiplier $1 - \mathcal{P}_L$ translates this into a positive cross-partial derivative for loan size: the fintech effect on I_L^* is larger at greater distance. The same logic applies to spreads: the proportional reduction in screening cost is greater for remote borrowers, generating a stronger spread compression. For high-risk borrowers, since $\partial C_H/\partial\phi = 0$ at all distances, there is no geographic amplification.

Prediction 4 (Cost channel: geographic reach)**.** *Under the cost-reduction channel:*

(a) $\partial\bar{d}_L/\partial\phi > 0$*: fintech expands the maximum lending distance for low-risk borrowers.*

(b) $\partial\bar{d}_H/\partial\phi = 0$*: the maximum lending distance for high-risk borrowers is independent of* ϕ*.*

The intuition is that digital screening flattens the cost gradient with respect to distance. Under relationship lending alone, screening costs grow with distance at rate γ. With fintech intensity ϕ, the expected cost $C_L = \phi c_D + (1-\phi)(c_0 + \gamma d)$ grows at the reduced rate $\gamma(1-\phi)$, because with probability ϕ the bank uses distance-independent digital screening. This flatter cost gradient extends the frontier of viable lending, enabling the bank to serve low-risk borrowers in

previously unreachable locations. Note that the effect is convex in ϕ—the $(1-\phi)^2$ term in the denominator of the derivative (see Appendix A.3) implies that geographic expansion accelerates as fintech intensity increases, since each additional increment of ϕ removes a larger share of the remaining distance-related cost. For high-risk borrowers, screening costs do not depend on ϕ, so the lending frontier is unchanged.

Prediction 5 (Cost channel: triple interaction)**.** *Under the cost-reduction channel, the geographic amplification of fintech effects is exclusive to low-risk borrowers, generating a positive triple interaction between fintech intensity, borrower type, and distance:*

$$\left.\frac{\partial^3 I^*}{\partial\phi\,\partial\mathbb{1}[\theta = L]\,\partial d}\right|_{\lambda=0} > 0 \tag{22}$$

The proof is given in Appendix A.4.

This triple interaction is the cost channel's sharpest empirical prediction. Fintech eliminates a cost disadvantage—distance-related screening expense—that only exists for borrowers who can be digitally assessed. Remote, low-risk borrowers experience the largest benefit because they bore the highest distance costs under the traditional screening regime; remote, high-risk borrowers experience no benefit at all because they cannot be screened digitally regardless of fintech intensity. The magnitude of the triple interaction is pinned down by $\gamma/(1-\mathcal{P}_L)$: it is larger when distance costs are steeper (high γ) and when the equity multiplier is larger (high $\mathcal{P}_L$), since the cost saving is amplified through leverage. This triple interaction is the key diagnostic that distinguishes the cost-reduction channel from the information-precision channel empirically.

3.4.2 Pure information-precision channel ($\lambda > 0$, no cost differential)

Now suppose fintech does not reduce screening costs (set $c_D = c_0$ and assume digital screening is never cheaper than relationship screening) but does improve signal precision: $\lambda > 0$ in equation (5). Under this channel, fintech improves the bank's ability to distinguish borrower types.

Prediction 6 (Precision channel: loan size)**.** *Under the information-precision channel:*

(a) $\partial I_L^*/\partial\phi > 0$*: fintech increases loan size for low-risk borrowers.*

(b) $\partial I_H^*/\partial\phi > 0$*: fintech also increases loan size for high-risk borrowers.*

The proof is given in Appendix A.5.

The key distinction from the cost channel is that improved signal precision benefits *both* borrower types. For low-risk borrowers, better signals move the posterior $\hat{p}_L$ closer to $p_L > \bar{p}$, raising pledgeable income and expanding borrowing capacity. For high-risk borrowers, better signals move $\hat{p}_H$ closer to $p_H < \bar{p}$; while this lowers their pooling subsidy, the resulting improvement in the bank's confidence about their type still expands lending on the margin of correctly identified high-risk borrowers who have positive NPV projects.[6]

Prediction 7 (Precision channel: spreads)**.** *Under the information-precision channel:*

(a) $\partial s_L/\partial\phi < 0$*: fintech reduces spreads for low-risk borrowers.*

(b) $\partial s_H/\partial\phi < 0$*: fintech also reduces spreads for high-risk borrowers.*

Higher precision raises $\hat{p}_\theta$, which increases the denominator of (21) and hence reduces the spread for both types.

Prediction 8 (Precision channel: geographic amplification)**.** *Under the information-precision channel:*

(a) $\partial^2 I_L^*/\partial\phi\,\partial d > 0$*: fintech effects on loan size are amplified at greater distance for low-risk borrowers.*

(b) $\partial^2 I_H^*/\partial\phi\,\partial d > 0$*: fintech effects on loan size are also amplified at greater distance for high-risk borrowers.*

The proof is given in Appendix A.6.

The geographic amplification under the precision channel arises through a fundamentally dif-

[6]Recall that under Assumption 1, high-risk projects have positive NPV ($p_H R > 1$), so a bank that correctly identifies a high-risk borrower is still willing to lend—albeit on terms that reflect the higher default probability.

ferent mechanism than under the cost channel. There is no mechanical distance × fintech interaction in screening costs, since the precision improvement $\lambda\phi$ is distance-independent. Instead, the amplification is driven by the *concavity of the equity multiplier* in signal precision: the multiplier $1/(1-\mathcal{P}_\theta)$ is convex in $\mathcal{P}_\theta$, so a given improvement in precision translates into a larger increase in loan size when baseline precision is low. Since baseline precision erodes with distance (α_θ^{eff} falls at rate β per unit of d), remote borrowers start from a lower precision baseline and therefore gain more from any given precision improvement. Critically, this mechanism operates for both borrower types, because distance degrades relationship screening quality equally for low- and high-risk borrowers. This stands in sharp contrast to the cost channel, where geographic amplification is exclusive to low-risk borrowers—a distinction that generates the divergent triple-interaction predictions exploited in our empirical identification.

Prediction 9 (Precision channel: triple interaction)**.** *Under the pure information-precision channel, the triple interaction between fintech intensity, borrower type, and distance is approximately zero:*

$$\left.\frac{\partial^3 I^*}{\partial\phi\,\partial\mathbb{1}[\theta=L]\,\partial d}\right|_{precision} \approx 0 \tag{23}$$

The proof is given in Appendix A.7.

The near-zero triple interaction under the precision channel reflects the fundamental symmetry of this mechanism: fintech improves signal quality by the same increment λ for all borrowers, and distance degrades baseline precision at the same rate β for all borrowers. The geographic amplification therefore applies approximately equally to low- and high-risk types, and the difference between the two—the triple interaction—washes out.[7] This stands in stark contrast to the cost channel, where the triple interaction is unambiguously positive (Prediction 5). The divergence between the two channels on this margin—a sharp positive triple interaction under cost reduction versus a near-zero one under information precision—provides the cleanest empirical diagnostic for distinguishing between mechanisms.

[7] A small positive triple interaction could emerge if the marginal value of precision differs across types due to their different baseline p_θ values, but this is a second-order effect that is quantitatively small relative to the first-order cost-channel prediction.

3.5 Nested model and empirical predictions

In practice, both the cost-reduction and information-precision channels may operate simultaneously. We therefore analyse the full nested model ($\lambda > 0$ and $c_D < c_0$) before deriving the empirical predictions that allow us to distinguish between channels. The pure cost-reduction channel ($\lambda = 0$) and the pure information-precision channel ($c_D = c_0$, no cost differential) emerge as special cases.

3.5.1 Nested model: both channels active

In practice, both channels may operate simultaneously: fintech may reduce screening costs for transparent borrowers *and* improve signal quality for all borrowers at the same time. We therefore analyse the full nested model with $\lambda > 0$ (active precision channel) and $c_D < c_0$ (active cost channel). The pure cost-reduction and pure information-precision channels studied in Sections 3.4.1 and 3.4.2 emerge as special cases when $\lambda = 0$ or $c_D = c_0$, respectively.

Loan size effects. In the nested model, the total effect of fintech on loan size operates through both the numerator and denominator of equation (18). To see this, recall that optimal loan size is $I_\theta^* = (A - C_\theta)/(1 - \mathcal{P}_\theta)$, where the numerator depends on screening costs and the denominator depends on signal precision through pledgeable income. Since fintech affects both C_θ and $\mathcal{P}_\theta$, differentiating with respect to ϕ using the quotient rule produces two additive terms—one for each channel.

For low-risk borrowers:

$$\frac{\partial I_L^*}{\partial \phi} = \underbrace{\frac{(c_0 + \gamma d) - c_D}{1 - \mathcal{P}_L}}_{\text{cost channel (numerator)}} + \underbrace{\frac{(A - C_L) \cdot \frac{\partial \mathcal{P}_L}{\partial \phi}}{(1 - \mathcal{P}_L)^2}}_{\text{precision channel (denominator)}} > 0 \tag{24}$$

The first term captures the cost-reduction channel. Fintech lowers the expected screening cost from $c_0 + \gamma d$ toward c_D, increasing effective equity by $(c_0 + \gamma d) - c_D$ per unit of fintech intensity. This additional equity is then leveraged by the multiplier $1/(1 - \mathcal{P}_L)$, translating the

cost saving into a larger total investment. The second term captures the information-precision channel. Better signals raise the bank's posterior $\hat{p}_L$ and hence pledgeable income $\mathcal{P}_L$, which increases the equity multiplier itself. The existing effective equity $(A - C_L)$ can now support a larger investment because each unit of equity covers a larger share of the financing gap. Both terms are strictly positive for low-risk borrowers, so the two channels reinforce each other. Moreover, the channels are *complementary*: the cost channel raises effective equity (the base being leveraged), while the precision channel raises the multiplier (the rate of leverage). A simultaneous improvement in both therefore generates a larger combined effect than the sum of the individual channels evaluated in isolation.

For high-risk borrowers, the cost channel is absent because digital screening is uninformative for opaque borrowers ($\partial C_H/\partial\phi = 0$):

$$\frac{\partial I_H^*}{\partial \phi} = \underbrace{0}_{\text{cost channel}} + \underbrace{\frac{(A - C_H) \cdot \lambda \left(R - \frac{B}{\Delta p}\right)}{(1 - \mathcal{P}_H)^2}}_{\text{precision channel}} \geq 0 \tag{25}$$

The entire effect on high-risk borrowers operates through the precision channel: fintech augments the relationship screening signal by λ (equation 5), raising pledgeable income by $\lambda(R - B/\Delta p)$ and hence increasing the equity multiplier. This effect is weakly positive—strictly so when $\lambda > 0$—but may be quantitatively small if the precision channel is weak relative to the cost channel.

The comparison of equations (24) and (25) yields a simple diagnostic. The ratio of the high-risk effect to the low-risk effect reveals the relative importance of the two channels. If the cost channel dominates (i.e., the first term in (24) is large relative to the second), then $\partial I_L^*/\partial\phi \gg \partial I_H^*/\partial\phi$ and fintech effects should be concentrated among low-risk borrowers. If instead the precision channel dominates (i.e., the second term in (24) is large relative to the first), then the high-risk and low-risk effects should be more symmetric, since both types benefit from improved signal quality. In the limiting case where $\lambda = 0$, the high-risk effect

vanishes entirely and all fintech effects are exclusive to low-risk borrowers.

Geographic interactions in the nested model. The same decomposition applies to the geographic amplification of fintech effects. The triple interaction—the extent to which the fintech × distance interaction differs across borrower types—is:

$$\frac{\partial^3 I^*}{\partial\phi\,\partial\mathbb{1}[\theta = L]\,\partial d} = \underbrace{\frac{\gamma}{1-\mathcal{P}_L}}_{\text{cost channel}} + \underbrace{\text{second-order terms}}_{\approx 0} \tag{26}$$

The cost channel contributes a first-order positive term proportional to γ, the marginal distance cost in relationship screening. This term arises because digital screening eliminates the distance component of costs for low-risk borrowers but not for high-risk borrowers, creating a type-specific geographic amplification (as shown in Prediction 5). The precision channel contributes only second-order terms, arising from differences in the curvature of the equity multiplier $(1 - \mathcal{P}_\theta)^{-2}$ across types due to their different baseline success probabilities. These second-order terms are quantitatively small relative to the first-order cost-channel contribution. A significant triple interaction is therefore primarily attributable to the cost-reduction channel even when both channels are active, making it a robust diagnostic regardless of whether the precision channel is also operative.

3.5.2 Empirical predictions

The nested model generates a rich set of testable predictions. Table 2 collects the full set, organised by the channel that drives each effect. Three predictions—marked as diagnostic tests—yield qualitatively different signs under the two channels and therefore allow the data to determine which mechanism dominates.

Diagnostic Test 1: High-risk borrower effects. Under the pure cost-reduction channel, fintech has zero effect on loan size, spreads, and lending probability for high-risk borrowers, since digital screening is uninformative for opaque borrowers (Predictions 1b and 2b). Under

Table 2: Model predictions and diagnostic tests

Prediction	**Cost reduction**	**Info precision**	**Empirical counterpart**	
Common predictions (both channels)				
$\partial I_L^*/\partial\phi$	>0	>0	Larger loans, low-risk	
$\partial s_L/\partial\phi$	<0	<0	Lower spreads, low-risk	
$\partial^2 I_L^*/\partial\phi\,\partial d$	>0	>0	Rural amplification, low-risk	
$\partial \bar{d}_L/\partial\phi$	>0	>0	Geographic reach, low-risk	
Diagnostic predictions (differ across channels)				
$\partial I_H^*/\partial\phi$	$=0$	>0	Loan size, high-risk	**Test 1**
$\partial s_H/\partial\phi$	$=0$	<0	Spreads, high-risk	**Test 1**
$\dfrac{\partial^3 I^*}{\partial\phi\,\partial\mathbb{1}[L]\,\partial d}$	>0	≈ 0	Triple interaction	**Test 2**
$\partial^2 I_H^*/\partial\phi\,\partial d$	$=0$	>0	Rural amplification, high-risk	**Test 3**
$\partial \bar{d}_H/\partial\phi$	$=0$	>0	Geographic reach, high-risk	**Test 3**

the information-precision channel, fintech improves signal quality for all borrowers, generating positive effects on high-risk lending outcomes (Predictions 6b and 7b). In the nested model, the magnitude of the high-risk effect relative to the low-risk effect identifies the contribution of the precision channel, since any effect on high-risk borrowers must originate from improved signal quality rather than cost reduction. Empirically, the absence of high-risk effects would be consistent with the cost-reduction mechanism and inconsistent with information-processing improvements.

Diagnostic Test 2: Triple interaction. Under the cost-reduction channel, the geographic amplification of fintech effects is exclusive to low-risk borrowers, generating a first-order positive triple interaction $\phi \times \mathbb{1}[\theta = L] \times d$ (Prediction 5). Under the information-precision channel, the geographic amplification applies approximately symmetrically to both borrower types, so the triple interaction is near zero (Prediction 9). In the nested model, a significant triple interaction is primarily attributable to the cost channel even when both mechanisms are active, since the precision channel's contribution to this margin is second-order (equation 26). A significant

triple interaction would support the cost-reduction interpretation over the information-precision mechanism.

Diagnostic Test 3: Geographic reach by borrower type. Under the cost-reduction channel, fintech expands the geographic radius of lending exclusively for low-risk borrowers, since only their screening costs decline with ϕ (Prediction 4). Under the information-precision channel, improved signal quality benefits borrowers of both types at all distances, expanding the lending frontier for both (Predictions 8 and 6). In the nested model, geographic expansion concentrated among low-risk borrowers points to cost reduction as the dominant mechanism; symmetric expansion across types points to information precision.

Taken together, the three diagnostic tests allow the data to determine the dominant channel. If the cost-reduction channel dominates, we expect: (i) zero or negligible effects on high-risk borrowers, (ii) a significant positive triple interaction, and (iii) geographic expansion concentrated among low-risk borrowers. If the information-precision channel dominates, we expect: (i) positive effects on high-risk borrowers, (ii) a near-zero triple interaction, and (iii) symmetric geographic expansion across borrower types. In the empirical analysis that follows, we implement all three tests. The results are consistent with the cost-reduction channel as the dominant mechanism: loan size and spread effects are concentrated among low-risk borrowers with no significant effects for high-risk borrowers, and the geographic amplification of fintech effects is likewise exclusive to the low-risk segment. These patterns align with the predictions of the cost-reduction channel across all three diagnostic margins.

4 Data

Our analysis draws on multiple data sources. We use monthly loan-level data from Experian, which capture granular details on loan amounts, repayment schedules, and borrower characteristics including arrears and geographic location. We complement this data with bank-level information from the Bank of England, providing monthly aggregates on SME and large corpo-

rate lending alongside relevant bank-specific control variables. We further augment our dataset with firm-level information from Bureau van Dijk's FAME database, which supplies additional borrower characteristics such as credit scores and total assets. To identify bank–FinTech partnerships, we compile information from CB Insights press releases.

4.1 Loan-level outcomes

We focus on unsecured commercial loans, which constitute the largest SME loan category in our data. Information asymmetries are most acute in this segment, as lenders must assess creditworthiness without the protection or screening benefits of collateral. Given that SMEs are typically informationally opaque, lacking extensive public financial information or long credit histories, the evaluation of unsecured credit is particularly challenging for traditional lending models. In the absence of collateral, unsecured lending is heavily dependent on soft information gathered through relationship lending (Berger and Udell, 1995, 2002). FinTech innovations in credit scoring directly address these information frictions, suggesting that technological adoption should have its most pronounced impact on unsecured SME lending.

Our analysis focuses on two key dependent variables measured at monthly frequency: commercial unsecured loan amounts at origination and commercial unsecured loan interest rates at origination, expressed as the spread over the 10-year gilt yield. Experian reports both the total debt outstanding (balance) and the total monthly repayments for each loan. To calculate interest rates, we proxy the first observable interest payment on each facility using the following relationship:

$$\text{Interest Payment} = \text{Total Payment} - \Delta\text{Balance} \tag{27}$$

where ΔBalance represents the change in the loan's outstanding balance and serves as a proxy for principal repayments. We assume that the first observed balance corresponds to the principal amount at origination. Given these measures, we calculate the interest rate at origination (in

percentage terms) as:

$$\text{Interest Rate} = \frac{\text{Interest Payment}}{\text{Balance at origination}} \times 100 \tag{28}$$

This approach allows us to construct consistent measures of both loan volumes and pricing across all loans in our sample. Table 3 shows some descriptive statistics on our variables of interest.

Table 3: Descriptive statistics for unsecured SME loans

	Mean	Median	Std. Dev.
Origination Volume (£)	202,000	20,300	697,000
Interest Rate (Annual, %)	11.30	8.20	16.67
Spread over 10-year gilt (%)	9.82	6.56	16.69

Source: Experian. Notes: Sample is limited to SMEs, defined as firms with fewer than 250 employees.

Our final dataset covers 19,998 SME loans for the period 2018-2023 across five leading UK SME lenders (Santander, Barclays, HSBC, Lloyds Banking Group, and NatWest). All loans in our final dataset include information on loan amounts, interest rates, bank identity, borrower characteristics, and timing. Using loan-level data allows us to explore heterogeneity across borrower risk categories and geographic locations, essential for understanding potential mechanisms behind the effects of FinTech adoption on SME lending. We exclude loans made under the Bounce Back Loan Scheme (BBLS), as these were not commercially priced and involved limited bank discretion due to government guarantees. While FinTech may have influenced BBLS disbursement, our focus is on credit supply dynamics under normal market conditions.

4.2 Measuring FinTech adoption by banks

Following Chernoff and Jagtiani (2023) and Jagtiani et al. (2025), we construct a measure of FinTech adoption by banks based on their business relationships with FinTech firms identified from press releases. Bank-FinTech partnerships take two main forms: strategic collaborations on core banking functions such as credit scoring and analytics (Jagtiani et al.,

2025), and formal alliances ranging from service provider contracts to equity investments (Klus et al., 2019). The approach often differs by size: banks frequently make equity investments in smaller FinTechs for strategic access to innovation, while forging product-specific collaborations with larger, established FinTechs to enhance their offerings (Hornuf et al., 2021).

These partnerships reflect complementary strategic needs. On the one hand, banks pursue both operational efficiencies—through access to digital solutions at lower cost and circumventing slow internal development processes—and strategic advantages, including accelerated innovation, shortened time-to-market, and enhanced competitive positioning via FinTech agility in responding to market dynamics (Klus et al., 2019; Jagtiani et al., 2025). On the other hand, FinTech firms pursue resource acquisition — including capital, established customer bases, data and infrastructure - to validate and scale their products. Partnering with reputable banks enhances their credibility among end-users, while banks' distribution networks and compliance capabilities provide critical synergies. Additionally, collaborations enable market learning, as banks offer customer entry points and feedback on market acceptance (Klus et al., 2019). Notably, Klus et al. (2019) find that banks' dominant motive is outsourcing rather than learning, suggesting that banks view these partnerships primarily as operational efficiency tools rather than as vehicles for transforming their internal information-processing capabilities.

We identify bank-FinTech partnerships using press releases from CB Insights covering the five leading UK banks in our sample from 2011 onward. Partnership activity prior to 2011 was negligible, making this an appropriate starting point for our analysis. We define FinTech-bank partnerships as business relationships involving knowledge transfer between FinTech developers and commercial banks, encompassing: (a) acquisitions of FinTech firms by banks; (b) strategic partnerships for product or platform development; (c) vendor agreements and licensing arrangements; and (d) venture capital investments by banks in FinTech firms. Unlike patent data, which indicates innovation but not necessarily active commercial use,

suffers from delays, and has identification challenges, our partnership-based measure captures actual operational relationships affecting lending practices in near real-time.

We manually classify the partnerships as pertaining to a number of different applications: (a) payment services, (b) savings and investments, (c) lending technologies (e.g., risk assessment platforms, digital underwriting systems), (d) customer service enhancements (e.g., chat bots), (e) client operations (e.g., advisory services, invoice insurance), and (f) bank operations (e.g., fraud detection). For our main analysis, we define a bank's FinTech intensity as the cumulative sum of its business relationships with FinTech developers pertaining to lending technologies (category c), ensuring our measure captures partnerships most directly relevant for SME credit provision. We identify 43 business relationships across the five leading UK SME lenders (Banco Santander, Barclays, HSBC, Lloyds Banking Group, and NatWest/RBS) during 2011–2023, of which 10 relate exclusively to lending technologies. Between 2018–2023 (time period for which Experian data is available), there were 26 business relationships, 8 relating to lending technologies. Figure 1 shows the distribution of partnerships across customer service applications (a-e). Partnerships pertaining to payment technologies are the most frequent, followed closely by partnerships pertaining to client operations and then lending/financing technologies.

Figure 2 shows the temporal pattern of FinTech-bank partnerships in our sample. Partnership activity remained minimal from 2012 to 2014, before accelerating sharply from 2015 onwards. The peak occurred in 2020 with 10 partnerships, likely reflecting pandemic-driven digital transformation efforts. Partnership formation has since declined, with only 3 new partnerships recorded in 2023.

Figure 1: Business relationships by customer service application (2011-2023)

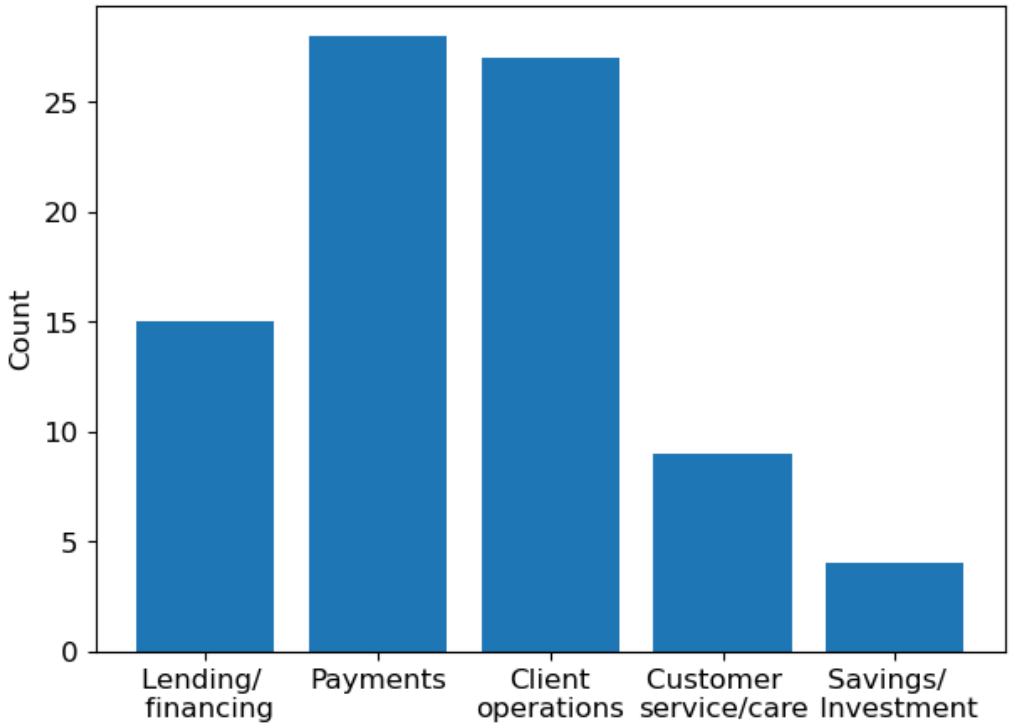
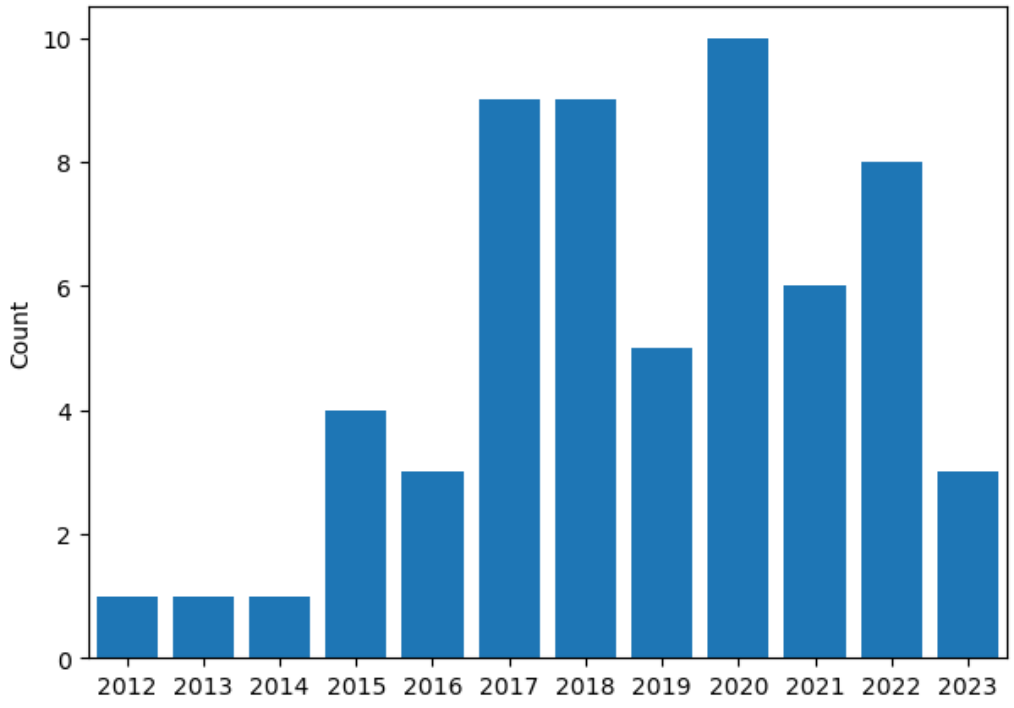


Figure 2: Bank-fintech business relationships over time



5 Empirical analysis

5.1 Loan volumes and pricing

We estimate panel regressions with granular fixed effects:

$$Y_{ijt} = \alpha + \beta_1 FI_{it} + \Gamma B_{it-1} + \Theta X_{jt-1} + \eta_{region} + \tau_{ind} + \lambda_{bank} + \gamma_{month} + \epsilon_{i,t} \tag{29}$$

The dependent variable Y_{ijt} is either the natural logarithm of the loan volume or the level of the spread at origination (in %) on a commercial unsecured loan from bank i to firm j at time t. FI_{it} is the variable of interest, namely the "FinTech intensity" of bank i at time t, defined as the cumulative sum of its business relationships with FinTechs (starting from 2011) up to time t. B_{it-1} are time-varying bank controls, including the capital ratio, the liquidity ratio, the log of assets, an HHI index of industry concentration of the bank's portfolio, and the share of SME loans in the bank's loan book (a measure of SME market specialisation). X_{jt-1} is a vector of firm controls, including the credit score, age, the log of assets, and a dummy variable equal to one when firm i is in receipt of a BBLS loan at time t, and zero otherwise. While we exclude BBLS loans from our analysis, we control for whether the borrowing firm received a BBLS loan. BBLS receipt signals pandemic-related financial distress that may independently affect commercial loan terms, and access to government-guaranteed funding may create substitution or complementarity effects in firms' demand for conventional commercial credit. We do not restrict our analysis to multi-bank firms and rely on firm fixed effects to absorb demand-side variation. Instead, we saturate the specification with granular fixed effects (region, industry, bank, and month-year) as in Degryse et al. (2019) to control for unobserved heterogeneity.

Table 4 presents our baseline results on the relationship between bank FinTech intensity and SME credit supply. The results indicate that FinTech partnerships significantly affect both the quantity and price of unsecured commercial lending to SMEs. The coefficient on FinTech intensity in the volume regression is 0.0633 (significant at the 1% level), indicating that each additional FinTech partnership is associated with a 6.3% increase in loan volumes.

Table 4: Effect of FinTech intensity on loan volumes and spreads

	Log(Volume)	**Spread**
Fintech intensity	0.0633***	-0.0918***
	(0.0168)	(0.0314)
Controls	Yes	Yes
Region FEs	Yes	Yes
Industry FEs	Yes	Yes
Provider FEs	Yes	Yes
Time FEs	Yes	Yes
Observations	19,998	19,998
R^2	0.71	0.23
Within R^2	0.55	0.01

Notes: Standard errors in parentheses clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1. Coefficients on control variables omitted for brevity.

This suggests that FinTech adoption meaningfully expands credit supply to SMEs. The effect on loan pricing is similarly pronounced. The coefficient of -0.0918 (significant at the 1% level) indicates that each additional FinTech partnership reduces loan spreads by approximately 9.2 basis points (11.7% compared to the mean spread). This pricing effect is economically significant: a bank with three FinTech partnerships would, on average, offer spreads nearly 28 basis points lower than a bank with no partnerships, holding all else constant.

Although not necessarily driven by the same mechanism, our findings that FinTech partnerships expand credit volume and reduce interest rates align with evidence that digital integration mitigates information asymmetry (Chen et al., 2025). The volume expansion also mirrors evidence that advanced IT capabilities substitute for physical branches to provide more competitive lending (Core and De Marco, 2024), and that higher IT adoption shields banks' ability to sustain lending during financial stress (Pierri and Timmer, 2022). Additionally, the reduction in spreads is consistent with AI and broadband-driven efficiencies that lower monitoring costs and borrowing rates (Piao et al., 2024; D'Andrea et al., 2025).

5.2 Heterogeneity by borrower risk

Next, we estimate Equation (29) across sub-samples defined by firms' creditworthiness, measured using the QuiScore at the time of loan origination. The QuiScore is a proprietary credit rating provided by BvD FAME, expressed on a 0–100 scale, where higher values indicate stronger financial health and lower credit risk. We classify borrowers into two groups: subprime, comprising firms in the bottom quartile of the QuiScore distribution, and prime, encompassing all others. Within the prime segment, we further examine each quartile to assess whether effects are concentrated at specific points along the risk spectrum.

Table 5: Effect by borrower risk - loan volumes

	Log(loan volume)					
	By credit rating			By risk quartile		
	Subprime	Prime	All	Q2	Q3	Q4
Fintech intensity	0.019	0.065***	0.063***	-0.001	0.068**	0.103***
	(0.034)	(0.019)	(0.017)	(0.033)	(0.032)	(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Provider FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,848	15,150	19,998	5,010	5,070	5,070
R^2	0.61	0.73	0.71	0.67	0.71	0.73
Within R^2	0.45	0.56	0.55	0.49	0.52	0.53

Notes: Standard errors in parentheses clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1. Coefficients on control variables omitted for brevity.

Tables 5 and 6 reveal that benefits accrue primarily to safer, more creditworthy firms. When splitting by credit rating, we find that FinTech partnerships significantly increase loan volumes (6.5%) and reduce spreads (12.4 basis points) for prime borrowers, while effects for subprime borrowers are statistically insignificant. The risk quartile analysis provides further granularity: FinTech intensity has no significant effect on the riskiest prime borrowers (Q1-Q2), but effects strengthen monotonically as borrower quality improves, with the largest impacts observed for the safest firms (Q4)—a 10.3% volume increase and 23.9 basis point spread reduction

per partnership. This pattern suggests that FinTech adoption disproportionately benefits high-quality borrowers who traditionally may have been underserved due to bank capacity constraints or the cost of manual underwriting, rather than expanding credit to marginal borrowers. The results are consistent with FinTech enabling operational efficiencies and faster processing that allow banks to scale up lending to safer firms, rather than with improved screening allowing banks to find creditworthy subprime borrowers. The absence of effects for subprime and lower-tier prime borrowers (Q1-Q2) suggests that FinTech partnerships do not materially alter banks' willingness to lend to riskier segments of the SME market.

Our finding that volume gains and spread reductions accrue primarily to prime borrowers aligns with evidence that IT enables efficient credit scaling for high-quality firms (Core and De Marco, 2024). However, our insignificant results for subprime borrowers contrast with evidence that AI, big data, and digital infrastructure can disproportionately expand credit to higher-risk firms or those with incomplete records (Jagtiani and Lemieux, 2019; Chen et al., 2025; D'Andrea et al., 2025), and with evidence that non-bank FinTech lenders using alternative data can identify creditworthy borrowers among those scored as subprime by traditional metrics (Cornelli et al., 2024).

5.3 Geographic inclusion

We test whether FinTech fosters geographic inclusion using the following model:

$$Y_{ijt} = \alpha + \beta_1 FI_{it} + \beta_2 A_{q1,rt} + \beta_3 (FI_{it} \times A_{q1,rt}) + \Gamma B_{it-1} + \Theta X_{jt-1} + \text{FEs} + \epsilon_{i,t} \tag{30}$$

$A_{q1,rt}$ is an indicator variable equal to one when a particular UK region is in the bottom quartile of population density, and zero otherwise. It is interacted with our measure of FinTech intensity. If FinTech promotes the inclusion of peripheral regions in credit markets β_3 should be positive for volumes and negative for spreads. In addition, since peripheral UK regions are well documented to have worse credit access, we expect β_2 to be negative for volumes and

Table 6: Effect by borrower risk - spreads

	Spread (pp)					
	By credit rating			By risk quartile		
	Subprime	Prime	All	Q2	Q3	Q4
Fintech intensity	0.055	-0.124***	-0.092***	0.001	-0.135**	-0.239***
	(0.083)	(0.034)	(0.031)	(0.045)	(0.056)	(0.072)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Provider FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,848	15,150	19,998	5,010	5,070	5,070
R^2	0.32	0.21	0.23	0.36	0.29	0.17
Within R^2	0.01	0.01	0.01	0.02	0.01	0.02

Notes: Standard errors in parentheses clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1. Coefficients on control variables omitted for brevity.

positive for spreads. We use low population density as an indicator of the rural character of a region, which itself is a proxy for lack of access to credit. Table 7 estimates Equation (30) using two alternative geographic classifications: ITL3 regions (columns 1, 3-4) and local authorities (columns 2, 5-6). Columns 3-6 further disaggregate the results by borrower credit quality.

In urban areas, a one-unit increase in FinTech intensity is associated with a 6.0% (ITL3 regions) or 5.6% (local authorities) increase in loan volume. The positive and significant interaction term between FinTech intensity and the rural dummy indicates that FinTech partnerships generate substantially larger effects in rural areas. The total effect in rural areas amounts to a 9.5% (ITL3: 0.060 + 0.035) or 11.4% (local authorities: 0.056 + 0.058) increase in loan volume per FinTech partnership. This near-doubling of the FinTech effect in rural areas is economically significant: a bank with three FinTech partnerships would increase lending volumes by approximately 18% in urban areas but by 29-34% in rural areas. The negative coefficient on the rural dummy confirms that SMEs in peripheral regions receive substantially smaller loans on average, consistent with limited banking infrastructure and potentially

higher screening costs in these areas. The coefficient of -0.107 (local authorities specification) indicates that rural firms receive approximately 10% smaller loans than observably similar urban firms.

Table 7: Geographic inclusion - loan volumes

	Log(loan volume)					
	All firms		By credit score			
	ITL3	Local	ITL3 regions		Local authorities	
	regions	authorities	Subprime	Prime	Subprime	Prime
Fintech intensity	0.060***	0.056***	0.016	0.059***	0.020	0.055***
	(0.018)	(0.017)	(0.036)	(0.020)	(0.034)	(0.020)
Rural dummy	-0.077***	-0.107***	-0.073	-0.091***	-0.006	-0.145***
	(0.027)	(0.029)	(0.052)	(0.031)	(0.057)	(0.033)
FI × Rural	0.035**	0.058***	0.040	0.040*	-0.002	0.075***
	(0.018)	(0.018)	(0.034)	(0.020)	(0.036)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Provider FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,501	19,998	4,731	14,770	4,848	15,150
R^2	0.71	0.71	0.61	0.73	0.61	0.73
Within R^2	0.56	0.55	0.45	0.56	0.45	0.56

Notes: Standard errors in parentheses clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1. Coefficients on control variables omitted for brevity.

The geographic inclusion effects are concentrated among prime (low-risk) borrowers. Columns 3 and 5 show that for subprime borrowers, FinTech intensity has no significant effect on loan volumes in either urban or rural areas, and the rural interaction term is small and statistically insignificant. In contrast, for prime borrowers (columns 4 and 6), FinTech intensity increases lending by 5.9% (ITL3) or 5.5% (local authorities) in urban areas, with the rural interaction adding an additional 4 percentage points (ITL3) or 7.5 percentage points (local authorities). For prime borrowers in rural areas using the local authorities definition, the total FinTech effect reaches 13% (0.055 + 0.075), more than double the urban effect.

This pattern presents a nuanced picture of financial inclusion through FinTech adoption. On one hand, FinTech partnerships appear to mitigate geographic barriers for previously underserved rural areas, consistent with improved credit assessment technologies reducing the cost of lending at distance and enabling banks to serve markets with limited branch presence. The disproportionate benefit to rural areas suggests that FinTech's comparative advantage lies in overcoming geographic information asymmetries rather than simply enhancing scale in already well-banked urban markets.

On the other hand, the concentration of benefits among prime borrowers indicates that FinTech adoption facilitates financial inclusion along the geographic dimension but not the credit risk dimension. Subprime borrowers—who face the most severe credit constraints and for whom information asymmetries are most acute—see no measurable benefit from FinTech partnerships. This suggests that while FinTech innovations improve banks' ability to assess and serve creditworthy borrowers at distance, they do not appear to relax credit constraints for the riskiest segment of the SME population. The lack of effects for subprime borrowers may reflect persistent information problems that even advanced analytics cannot fully resolve, or banks' strategic focus on expanding lending to lower-risk segments where regulatory capital requirements are less binding. The robustness of these patterns across both geographic classifications (ITL3 regions and local authorities) strengthens confidence in the findings. We find no corresponding heterogeneous effects on loan spreads (results available upon request), suggesting that the geographic dimension primarily affects credit quantities rather than prices.

Our findings distinguish financial inclusion across geographic and credit risk dimensions. The mitigation of geographic barriers in rural areas aligns with Core and De Marco (2024) and Kutzbach and Pogach (2024), who show that IT enables banks to extend lending beyond their branch footprint. Piao et al. (2024) further confirm that AI enables lending in poorer, distant regions. However, the concentration of benefits among prime borrowers is consistent with the cost-reduction mechanism documented in Core and De Marco (2024), where IT

primarily facilitates lending to borrowers who can be assessed without proximity-dependent soft information, but contrasts with D'Andrea et al. (2025) and Chen et al. (2025), who find that technology disproportionately expands credit to high-risk or information-poor firms. The geographic inclusion we document for bank-adopted FinTech is consistent with evidence that non-bank FinTech lenders also concentrate lending in underserved areas with higher unemployment and bankruptcy rates (Cornelli et al., 2024). However, unlike non-bank FinTech platforms—which can extend credit to borrowers scored as subprime by traditional metrics by leveraging alternative data and proprietary scoring models (Cornelli et al., 2024; Jagtiani and Lemieux, 2019)—bank-adopted FinTech in our setting benefits only prime borrowers, suggesting that regulatory constraints or banks' reliance on traditional credit scores may limit the credit-risk inclusion channel.

5.4 Fintech as a substitute for physical presence

We investigate whether fintech enables banks to extend credit to regions in which they lack physical branch presence. The spatial lending literature establishes that loan pricing and availability depend critically on geographic distance and local competitive structure. Degryse and Ongena (2005) provide comprehensive evidence of spatial price discrimination in Belgian bank lending to small firms: loan rates decrease with borrower-lender distance and increase with the distance to competing banks, reflecting the market power that banks derive from the transportation costs faced by proximate borrowers with limited outside options. Their finding that transportation costs—rather than informational asymmetries—drive the observed spatial pricing patterns is consistent with the cost-based mechanism at the core of our model. In a complementary vein, Petersen and Rajan (2002) document that the distance between small firms and their lenders grew steadily over 1973–1993, a trend correlated with rising bank productivity driven by information technology, and that distance became a weaker predictor of borrower credit quality over time. At the same time, Nguyen (2019) demonstrate that branch closures reduce small business credit origination—an effect that persists even when replacement branches enter, indicating destruction of relationship-specific soft information

rather than merely diminished competition. This is consistent with the broader insight of Berger and Udell (2002) that soft information accumulated through relationship lending may be lost when banking structures change, since the loan officer is the primary repository of this non-transferable information.

Our findings—that fintech adoption increases loan volumes and reduces spreads, with effects concentrated among low-risk borrowers in rural areas—are consistent with a cost-reduction mechanism through which technology eliminates distance-dependent screening expenses. This cost reduction generates two complementary effects. First, banks can profitably lend to creditworthy borrowers in previously unviable markets, particularly rural areas with sparse branch networks (volume effect). Second, lower marginal costs enable reduced spreads while maintaining profitability (price effect). These are not competing explanations but two manifestations of a unified supply curve shift: fintech-enabled cost reduction simultaneously expands market reach and improves pricing.

We find evidence supporting this mechanism in Table 8. The positive and significant coefficients on FinTech intensity confirm that adoption of FinTech innovations is associated with increased loan volumes for prime borrowers. Branch closures exert a significant negative effect on lending to prime borrowers (columns 4 and 6), consistent with the destruction of soft information documented by Nguyen (2019), but this effect is substantially offset in markets where banks have adopted FinTech. The interaction term between FinTech intensity and branch closures is positive and significant at the ITL3 regional level (columns 1 and 4) and marginally significant for local authorities (columns 2 and 6), suggesting that FinTech mitigates the adverse credit supply effects of branch closures.

While bank branch closures typically reduce credit supply due to the loss of "soft information", our results demonstrate that bank FinTech intensity significantly offsets this negative impact. This supports the argument by Core and De Marco (2024) that IT capabilities can substitute for a physical presence in credit provision. Furthermore, it aligns with Kutzbach and Pogach

Table 8: Branch closures and FinTech lending

	log(loan volume)					
	All firms		By credit score			
	ITL3	LA	ITL3		LA	
	(1)	(2)	(3) Subprime	(4) Prime	(5) Subprime	(6) Prime
Fintech intensity (FI)	0.044**	0.052***	0.016	0.041*	0.013	0.055***
	(0.020)	(0.018)	(0.039)	(0.022)	(0.037)	(0.021)
Branch closures (per 1000)	−1.589	−1.649	0.307	−2.122*	1.031	−2.649*
	(1.052)	(1.366)	(1.777)	(1.221)	(2.613)	(1.572)
FI × Branch closures	1.598**	1.421	0.355	1.934***	0.850	1.299
	(0.724)	(0.885)	(1.076)	(0.688)	(1.750)	(1.018)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,477	19,907	4,730	14,747	4,830	15,077
R^2	0.712	0.712	0.614	0.727	0.613	0.727
Within R^2	0.556	0.554	0.454	0.561	0.453	0.558

Notes: Clustered standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Branch closures measured at ITL3 level in columns (1), (3)–(4) and local authority (LA) level in columns (2), (5)–(6). Control variables omitted for brevity.

(2024), who find that technology enhances banks' capacity for out-of-area lending.

Critically, however, this mechanism operates only for digitally assessable borrowers—those whose creditworthiness can be evaluated using hard information and automated credit scoring. This suggests that high-risk SMEs continue to require relationship-based assessment involving soft information gathered through repeated personal interactions, which does not scale digitally regardless of the underlying cost structure. This explains why our heterogeneity analysis shows effects concentrated exclusively among low-risk borrowers in the top quartiles of the credit score distribution. FinTech complements rather than substitutes for traditional relationship lending, expanding banks' geographic reach for standardized credit products while preserving the necessity of branch-based assessment for opaque, high-risk borrowers.

6 Conclusions

This paper provides novel evidence on how FinTech adoption by traditional banks affects SME lending. Using granular loan-level data and a partnership-based measure of FinTech intensity, we document three key findings that present a nuanced picture of financial inclusion through technological innovation. First, FinTech adoption enables banks to extend larger loans at lower spreads to SMEs. These effects are economically meaningful and suggest that partnerships with FinTech firms meaningfully expand credit supply while improving terms for borrowers. Second, we find evidence of geographic but not credit risk inclusion. FinTech partnerships generate substantially larger effects in rural, low population-density regions, suggesting that digital technologies help overcome traditional geographic constraints in SME finance. However, these benefits accrue exclusively to low-risk borrowers. We find no evidence that FinTech adoption expands lending to subprime firms, even in underserved regions. This heterogeneity indicates that while FinTech innovations reduce geographic information asymmetries, they do not resolve fundamental opacity problems for the riskiest SMEs. Third, we identify a mechanism underlying these patterns: FinTech enables banks to maintain lending relationships despite branch network contraction. In regions experiencing branch closures, FinTech-adopting banks sustain credit supply to prime borrowers, consistent with digital technologies substituting for physical infrastructure in serving digitally assessable firms.

Our findings contribute to the literature by providing the first comprehensive evidence on bank-adopted FinTech's impact on SME lending, isolating technology effects from regulatory differences between banks and non-bank FinTech lenders. The results suggest that FinTech can help address the longstanding SME financing gap and promote geographic inclusion without increasing bank risk-taking. However, technology alone does not expand access for the most credit-constrained borrowers—those facing fundamental information asymmetries rather than geographic barriers. This finding echoes evidence from the US mortgage market, where Fuster et al. (2019) similarly find little evidence that FinTech lenders are more effective at allocating credit to borrowers with low access to finance, despite offering

a faster and more efficient origination process. Complementary policies may be needed to address persistent credit constraints for opaque, high-risk SMEs who remain underserved even as FinTech reshapes traditional banking.

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A Proofs of model predictions

This appendix collects the formal proofs of all predictions stated in Section 3.4.

A.1 Proof of Prediction 1 (Cost channel: loan size)

Recall from equation (18) that optimal loan size is $I_\theta^* = (A - C_\theta)/(1 - \mathcal{P}_\theta)$.

Part (a): Low-risk borrowers. Differentiating the expected screening cost in equation (6) with respect to ϕ gives:

$$\frac{\partial C_L}{\partial \phi} = c_D - (c_0 + \gamma d) < 0 \tag{31}$$

since digital screening is cheaper than relationship screening ($c_D < c_0$) and eliminates the distance component (γd). With $\lambda = 0$, signal precision is independent of ϕ, so the denominator of (18) is unaffected. The entire effect of fintech on low-risk loan size therefore operates through the numerator—increased effective equity:

$$\left.\frac{\partial I_L^*}{\partial \phi}\right|_{\lambda=0} = \frac{(c_0 + \gamma d) - c_D}{1 - \mathcal{P}_L} > 0 \tag{32}$$

The numerator is the screening cost saving, and the denominator is the financing gap per unit of investment, which is strictly positive under Assumption 2 (i.e., $\mathcal{P}_L < 1$). The multiplier $1/(1 - \mathcal{P}_L)$ amplifies the cost saving into a larger investment increase. □

Part (b): High-risk borrowers. Screening costs are $C_H = c_0 + \gamma d$ from equation (7), which does not depend on ϕ since digital screening is uninformative for opaque borrowers. The denominator is likewise unaffected (since $\lambda = 0$), so $\partial I_H^*/\partial \phi = 0$. High-risk borrowers are entirely untouched by the cost-reduction channel. □

A.2 Proof of Prediction 3 (Cost channel: geographic amplification)

Part (a): Low-risk borrowers. The cross-partial of screening cost for low-risk borrowers is:

$$\frac{\partial^2 C_L}{\partial \phi \, \partial d} = \frac{\partial}{\partial d}\left[c_D - (c_0 + \gamma d)\right] = -\gamma < 0 \tag{33}$$

That is, the cost saving from fintech grows with distance at rate γ. Since $\lambda = 0$, the denominator of (18) is independent of both ϕ and d conditional on type, so the cross-partial of loan size inherits the sign directly:

$$\left.\frac{\partial^2 I_L^*}{\partial \phi \, \partial d}\right|_{\lambda=0} = \frac{\gamma}{1 - \mathcal{P}_L} > 0 \tag{34}$$

□

Part (b): High-risk borrowers. $C_H = c_0 + \gamma d$ is independent of ϕ at all distances, so $\partial^2 C_H / \partial \phi \, \partial d = 0$ and hence $\partial^2 I_H^* / \partial \phi \, \partial d = 0$. □

A.3 Proof of Prediction 4 (Cost channel: geographic reach)

The maximum lending distance $\bar{d}_\theta$ is defined by the condition $A - C_\theta(\bar{d}_\theta, \phi) = 0$, i.e., the distance at which screening costs exhaust the entrepreneur's wealth.

Part (a): Low-risk borrowers. Setting $A = \phi c_D + (1 - \phi)(c_0 + \gamma \bar{d}_L)$ and solving for $\bar{d}_L$ gives:

$$\bar{d}_L(\phi) = \frac{A - \phi c_D - (1 - \phi) c_0}{\gamma (1 - \phi)} \tag{35}$$

Differentiating with respect to ϕ:

$$\frac{\partial \bar{d}_L}{\partial \phi} = \frac{A - c_D}{\gamma (1 - \phi)^2} > 0 \tag{36}$$

which is strictly positive since $A > c_D$ (screening cost must be less than borrower wealth for any lending to occur). □

Part (b): High-risk borrowers. $C_H = c_0 + \gamma d$ is independent of ϕ, so $\bar{d}_H = (A - c_0)/\gamma$ and $\partial \bar{d}_H / \partial \phi = 0$. □

A.4 Proof of Prediction 5 (Cost channel: triple interaction)

The triple interaction is the difference in the fintech × distance interaction across borrower types. From Prediction 3 (proved in Appendix A.2):

$$\left.\frac{\partial^2 I_L^*}{\partial \phi \, \partial d}\right|_{\lambda=0} = \frac{\gamma}{1 - \mathcal{P}_L} > 0 \qquad \text{and} \qquad \left.\frac{\partial^2 I_H^*}{\partial \phi \, \partial d}\right|_{\lambda=0} = 0 \tag{37}$$

The triple interaction is the difference between these two terms:

$$\left.\frac{\partial^3 I^*}{\partial \phi \, \partial \mathbb{1}[\theta = L] \, \partial d}\right|_{\lambda=0} = \frac{\gamma}{1 - \mathcal{P}_L} - 0 = \frac{\gamma}{1 - \mathcal{P}_L} > 0 \tag{38}$$

□

A.5 Proof of Prediction 6 (Precision channel: loan size)

With no cost differential, the numerator of (18) is unaffected by ϕ for both types. The effect operates entirely through the denominator.

Part (b): High-risk borrowers. From (11), $\partial \alpha_H^{eff} / \partial \phi = \lambda > 0$. This raises the posterior:

$$\frac{\partial \hat{p}_H}{\partial \phi} = \lambda (p_H - \bar{p}) \tag{39}$$

Since $p_H < \bar{p}$, we have $\partial \hat{p}_H / \partial \phi < 0$. However, this reflects the correction of the adverse selection subsidy: the bank was previously overestimating high-risk borrowers' quality due to pooling.[8]

[8]The result $\partial \hat{p}_H / \partial \phi < 0$ means the bank's assessment of identified high-risk borrowers moves closer to their true (lower) success probability. But the bank is now *more confident* in this assessment, which raises pledgeable income for correctly identified high-risk borrowers because the bank faces less uncertainty about expected repayment. In the model, we consider the lending decision conditional on the borrower being correctly identified as type θ, so the relevant posterior is $\hat{p}_H(\alpha) = \alpha_H^{eff} \cdot p_H + (1 - \alpha_H^{eff}) \cdot \bar{p}$, and what matters for pledgeable income is the precision-weighted posterior evaluated at the true type, not the direction of the posterior shift per se.

For the pledgeable income relevant to the lending decision (conditional on the borrower being correctly identified), we have:

$$\frac{\partial \mathcal{P}_H}{\partial \phi} = \lambda(p_H - \bar{p}) \left(R - \frac{B}{\Delta p} \right) \tag{40}$$

Under Assumption 1 and the fact that the bank lends to correctly identified high-risk borrowers (since $p_H R > 1$), the increase in signal precision $\lambda > 0$ raises pledgeable income $\mathcal{P}_H$. To see this more directly: with better precision, the bank can more accurately price high-risk loans at their true risk (p_H), which increases confidence in expected repayment relative to the pooled prior, expanding the equity multiplier $1/(1 - \mathcal{P}_H)$ and hence I_H^*.

Part (a): Low-risk borrowers. Precision also improves, increasing I_L^* through the same multiplier channel. Since $p_L > \bar{p}$, we have $\partial \hat{p}_L / \partial \phi = \lambda(p_L - \bar{p}) > 0$, so the posterior moves toward the (higher) true success probability, unambiguously raising pledgeable income and loan size. □

A.6 Proof of Prediction 8 (Precision channel: geographic amplification)

With no cost differential, fintech affects loan size entirely through the denominator of (18). Differentiating $I_\theta^* = (A - C_\theta)/(1 - \mathcal{P}_\theta)$ with respect to α_θ^{eff} gives the marginal value of precision:

$$\frac{\partial I_\theta^*}{\partial \alpha_\theta^{eff}} = \frac{(A - C_\theta)(p_\theta - \bar{p}) \left(R - \frac{B}{\Delta p} \right)}{(1 - \mathcal{P}_\theta)^2} \tag{41}$$

For low-risk borrowers ($p_L > \bar{p}$), this is strictly positive. For high-risk borrowers ($p_H < \bar{p}$), the sign of the numerator is negative, but the relevant consideration for the lending margin is that the bank's confidence in its assessment improves, raising the effective pledgeable income for correctly screened borrowers. In the model's reduced-form expression, what matters is the total derivative of I_θ^* with respect to ϕ, which operates through $\partial \mathcal{P}_\theta / \partial \phi > 0$ for both types (as

established in the proof of Prediction 6).

The key result is that the marginal value of precision is proportional to $(1 - \mathcal{P}_\theta)^{-2}$. Since baseline precision declines with distance ($\partial \alpha_\theta^{eff} / \partial d = -\beta < 0$), $\mathcal{P}_\theta$ is lower at greater d, making $(1 - \mathcal{P}_\theta)^{-2}$ larger. Meanwhile, the precision improvement from fintech, $\partial \alpha_\theta^{eff} / \partial \phi = \lambda$, is distance-independent. The cross-partial is therefore:

$$\frac{\partial^2 I_\theta^*}{\partial \phi \, \partial d} = \lambda \cdot \frac{\partial}{\partial d} \left[\frac{(A - C_\theta)(p_\theta - \bar{p}) \left(R - \frac{B}{\Delta p} \right)}{(1 - \mathcal{P}_\theta)^2} \right] > 0 \tag{42}$$

which is positive for both $\theta \in \{L, H\}$ because the increase in $(1 - \mathcal{P}_\theta)^{-2}$ at greater distance raises the marginal value of the precision improvement λ. □

A.7 Proof of Prediction 9 (Precision channel: triple interaction)

The triple interaction is the difference in the fintech × distance interaction across borrower types. From Prediction 8 (proved in Appendix A.6), the precision channel generates geographic amplification for both types:

$$\left. \frac{\partial^2 I_\theta^*}{\partial \phi \, \partial d} \right|_{\text{precision}} = \lambda \cdot \frac{\partial}{\partial d} \left[\frac{(A - C_\theta)(p_\theta - \bar{p}) \left(R - \frac{B}{\Delta p} \right)}{(1 - \mathcal{P}_\theta)^2} \right] > 0 \quad \text{for } \theta \in \{L, H\} \tag{43}$$

Both expressions share the same first-order structure: the precision improvement λ is type-independent, and the distance erosion of baseline precision ($-\beta$) is also type-independent. The two cross-partials therefore differ only to the extent that the level of $\mathcal{P}_\theta$ differs across types (since $p_L \neq p_H$), which affects the curvature of the multiplier $(1 - \mathcal{P}_\theta)^{-2}$. This residual difference is second-order relative to the first-order geographic amplification that is common to both types:

$$\left. \frac{\partial^3 I^*}{\partial \phi \, \partial \mathbb{1}[\theta = L] \, \partial d} \right|_{\text{precision}} = \frac{\partial^2 I_L^*}{\partial \phi \, \partial d} - \frac{\partial^2 I_H^*}{\partial \phi \, \partial d} \approx 0 \tag{44}$$

□