Technology, Online Banks, and Credit Market Segmentation

Laura Bottazzi* Chiara Farronato† Rachel J. Nam‡ Loriana Pelizzon§

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Abstract

How does online bank development (digital-only depository institutions that originate loans without human intermediation) affect consumer credit market structure? Using loan-level data from Germany, we show that online banks cherry-pick low-risk borrowers, generating adverse selection for traditional banks. We develop and test a model in which online banks have lower costs but weaker screening because they rely solely on hard information. Online banks offer substantially lower rates to low-risk borrowers, but this advantage declines with credit risk, creating a crossover point beyond which traditional banks become more competitive. Using historical branch density as an instrument, we show that supply-driven screening differences contribute to this pattern. Extending the framework to fintech lenders reveals market segmentation: online banks serve the lowest-risk borrowers, traditional banks the medium-risk segment, and fintechs the highest-risk segment. Over time, the traditional online rate gap widens, consistent with deteriorating borrower pools at traditional banks. Our findings highlight that technological development in credit markets can generate important distributional consequences.

Keywords: Banks, Online Banks, FinTech, Credit Market Segmentation, Digital Platforms, Adverse Selection
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*Bologna University, Piazza Scaravilli 2, Bologna, Italy.
†Harvard Business School, Harvard University, Boston, Massachusetts 02163, United States.
‡USI Lugano and Swiss Finance Institute. Via Giuseppe Buffi 6, 6900 Lugano, Switzerland. Corresponding author email: rachel.nam@usi.ch
§Leibniz Institute for Financial Research SAFE & Goethe University Frankfurt, Theodor-W.-Adorno-Platz 3, 60323 Frankfurt am Main, Germany

1 Introduction

Consumer credit markets have undergone a significant transformation in recent years. Technological advances have enabled the emergence of online banks, digital-only depository institutions that originate loans without human intermediation, and fintech lending platforms operating under lighter regulatory regimes (Buchak, Matvos, Piskorski, and Seru, 2018; de Roure, Pelizzon, and Thakor, 2022). Unlike traditional banks that rely on branch networks and relationship banking, these new entrants originate loans exclusively through digital platforms.

Two stylized facts in the German consumer credit market motivate our research. First, online bank lending has grown rapidly over the past decade, while traditional bank lending has stagnated or declined (Figure 1). Second, the data reveal clear rate stratification: online banks offer the lowest rates, traditional banks charge intermediate rates, and fintechs charge the highest (Figure 2).

These patterns raise a central question: why do online banks offer lower rates? We show it reflects both cost advantages and cherry picking. Online banks operate with lower costs due to the absence of branches, but also screen borrowers using only hard information—a technology effective for identifying prime borrowers who look good on paper, but inadequate for distinguishing among borrowers at higher risk levels where soft information matters. This concentrates online banks in the low-risk segment. As they capture the safest borrowers, traditional banks are left serving a riskier pool. The result is a segmented market: online banks specialize in the low-risk, traditional banks serve the middle, and fintechs expand the market toward the high-risk that banks decline.

To guide our empirical analysis, we develop a simple model of competition in credit markets. Borrowers differ in default risk, which is partially observable through hard information. Three lender types compete. Online banks have lower operational costs but screen using only hard information. Traditional banks have higher costs but can use soft information obtained through branch networks. Fintechs have superior technology and lower regulatory costs, making it profitable to serve high-risk borrowers that banks decline. A key assumption is that online banks face a screening disadvantage. This is motivated by conversations with industry insiders, who confirm that online banks employ simple, rule-based screening processes rather than sophisticated algorithms. Hard information suffices to identify prime borrowers, but becomes inadequate at higher risk levels where distinguishing among borrowers requires soft information from relationships and local market knowledge. This asymmetry generates market segmentation across borrower risk profiles.

The model yields three testable predictions. First, market segmentation arises across lender types. Online banks concentrate in the low-risk segment where hard-information screening is sufficient and their cost advantage dominates. Traditional banks serve

medium-risk borrowers, where soft information becomes valuable. Fintechs operate in the high-risk segment, where their superior technology and lower regulatory costs make lending profitable. Second, online banks' rate advantage declines with borrower risk, generating a crossover point. At low risk levels, online banks exploit their cost advantage to undercut traditional banks. But as risk increases, their screening disadvantage becomes binding—traditional banks' ability to use soft information grows more valuable, while online banks' cost advantage becomes less important (Petersen and Rajan, 1994). Beyond a threshold, traditional banks offer lower rates, and online banks rationally exit. Third, as online banks capture the safest borrowers, the risk composition of traditional banks' borrower pools worsens. This adverse selBeyhaghiection is reflected in rising rates for traditional banks over time.

We test these predictions using loan-level data from the German consumer credit market. The data are collected from the European Data Warehouse (EDW), a securitization repository designated by the European Securities and Markets Authority (ESMA) and the German Federal Financial Supervisory Authority (BaFin). The data contain loan-level information for loans originated by online banks, traditional banks, and fintech platforms. Although this is a sample of the full market, the EU Securitisation Regulation requires these loans to be representative of each lender's portfolio, making the data well-suited to study the composition of borrowers across lender types.

The empirical analysis confirms the model's predictions. First, the data reveal sharp segmentation in borrower pools across lender types. Online banks concentrate overwhelmingly in the lowest-risk segment—about 80% of their loans go to borrowers with estimated default probability below 1%—while traditional banks serve a riskier and more dispersed pool. The median default probability is 0.4% for online-bank borrowers versus 2.8% for traditional-bank borrowers, with limited overlap across the distributions. Second, interest rate differentials between online and traditional banks exhibit a clear crossover pattern. Online banks charge substantially lower rates for low-risk borrowers, but their advantage shrinks rapidly with borrower risk. Around a 3.2% default probability, traditional banks offer lower rates than online banks—consistent with the fact that online banks mostly lend to borrowers with default probability below 2.5%. Third, we find evidence of adverse selection effects on traditional banks following online bank expansion. Conditional on risk, the rate differential between traditional and online banks has widened over time—from about 209 basis points in 2019 to 455 basis points in 2025. This widening cannot be fully explained by differential pass-through of monetary policy, suggesting that traditional banks face a progressively deteriorating borrower pool as online banks cherry-pick safer borrowers. Finally, we confirm that fintech lending expands the market toward the highest-risk borrowers (de Roure, Pelizzon, and Thakor, 2022).

While we emphasize supply-side screening as the mechanism generating market segmentation, demand-side sorting may also reinforce these patterns. Household survey data

from the Bundesbank shows that consumers whose primary bank is an online bank tend to be higher-income, more educated, and younger (more technologically savvy)—traits positively correlated with creditworthiness. Yet, these same households face higher rejection rates for credit, suggesting that online banks apply stringent screening even among their favorably selected applicant pool.

To formally isolate the supply-side component, we implement an instrumental variables strategy that exploits cross-district variation in historical bank branch density. In districts with fewer branches, the higher transaction and application costs of borrowing through traditional bank branches induce some borrowers to switch to online lenders. In this framework, branch scarcity acts as an exogenous shifter of lending channel choice, allowing us to separate supply-driven screening from endogenous borrower sorting. The instrument is constructed by interacting 2017 branch density at the district level with indicators for low- and mid-risk borrowers, where risk is measured using predicted default probability solely based on observables. This generates segment-specific instruments that shift online bank usage within each risk bin.

The first stage confirms that historical branch density strongly predicts online bank borrowing. In other words, borrowers in districts with fewer branches are significantly more likely to borrow from online banks. Importantly, the predicted shift toward online banks is substantially larger for low-risk borrowers than for mid-risk borrowers. This heterogeneity is informative in understanding the drivers of market segmentation. If the observed segmentation were driven solely by low-risk borrowers actively selecting into online banks, then an external shifter of lending channel—such as branch scarcity—should move low- and mid-risk borrowers toward online banks by comparable magnitudes. The attenuated response among mid-risk borrowers instead suggests that even when traditional borrowing becomes more costly, these borrowers are less able to move into online banks, consistent with supply-side screening constraints that bind more strongly outside the low-risk segment. In the second stage, we show that low-risk borrowers pay significantly lower interest rates, while mid-risk borrowers experience no comparable rate advantage. This result mirrors the reduced-form results and supports a supply-side screening-based mechanism.

In our IV estimation, the identifying assumption is that historical branch density affects current loan pricing only through its effect on lending channel choice. A exclusion restriction violation would arise if branch density directly influences interest rates independent of channel switching. For example, districts with historically fewer branches may exhibit persistently weaker local banking competition, allowing traditional banks to charge higher rates. In that case, the IV would partly capture inflated traditional-bank pricing rather than the effect of switching into online banks, biasing the estimated online rate advantage upward. Similarly, if historical branch networks proxy for slow-moving local economic conditions or unobserved borrower quality that directly affect loan pricing,

the instrument could be correlated with the error term, again inflating the IV estimates.

To address these concerns, we saturate the specification with federal-state fixed effects—capturing persistent regulatory and institutional differences across states—along with loan-origination-year fixed effects, employment status fixed effects, and pre-sample district-level controls for GDP, population density, and employment to absorb slow-moving local economic conditions that may be correlated with historical branch networks. Standard errors are clustered at the district level. We further conduct falsification tests restricted to traditional bank loans. Conditional on the full set of controls, historical branch density does not predict traditional-bank interest rates or default outcomes. These results mitigate concerns that the instrument captures local market power or unobserved borrower risk rather than channel switching. Taken together, the IV evidence indicates that supply-driven screening contributes to online banks' concentration in the low-risk segment and the resulting rate differentials.

Finally, to provide causal evidence that online bank expansion worsens traditional banks' borrower pools, we implement a shift-share design that exploits differential rates of branch network consolidation across German banking groups. Actual district-level branch closures are endogenous—banks may close branches in response to local economic deterioration that independently affects borrower quality. The shift-share construction addresses this by decomposing district-level branch losses into two components: pre-determined local banking group shares that reflect the historical structure of each district's branch network, and national-level closure rates driven by corporate restructuring decisions—such as the Deutsche Bank–Postbank integration—rather than by conditions in any individual district. German banking groups have consolidated at sharply different rates between 2017 and 2024, ranging from approximately 68% for big banks to roughly 32% for savings banks and cooperatives. We combine these differential national closure rates with the pre-determined district-level shares to construct a measure of predicted exposure to branch consolidation that varies across districts and years, allowing us to absorb district and year fixed effects.

We show that districts more exposed to predicted branch losses see higher predicted default probabilities among traditional bank borrowers, consistent with online bank expansion drawing low-risk borrowers away from traditional lenders as branch access declines. To address the concern that the exposure measure captures local economic deterioration rather than channel switching, we run a placebo test on online bank borrowers and find no effect on their borrower composition. Taken together, our findings indicate that technological development in credit markets can drive market segmentation, with potentially unintended consequences for adverse selection and distributional consequences.

We contribute to the growing literature on the impact of digital transformation in credit markets, with a particular focus on digital-only banks. A growing body of literature examines how online banks and digital platforms affect deposit markets and bank

competition. Erel, Liebersohn, Yannelis, and Earnest (2023) show that online banks offer significantly higher deposit rates than traditional banks due to increased competition and reduced search costs, allowing them to rapidly adjust rates in response to monetary policy changes. Kundu, Muir, and Zhang (2024) document a structural divergence in the banking sector between high-rate banks, which operate primarily online, hold shorter-term assets, and take more credit risk through personal loans, and low-rate banks, which rely on sticky deposits and hold longer-term securities. They show that technological advancements enabled this divergence, with high-rate online banks attracting less sticky depositors. Other studies examine traditional banks' adoption of digital technologies. Jiang, Yu, and Zhang (2022) show that digital disruption leads banks to close branches and increasingly specialize in serving distinct customer segments. Amberg and Becker (2024) show that this shift can constrain credit access for small and medium-sized enterprises, with important implications for welfare and financial inclusion. Koont (2023) studies digital platform adoption by U.S. banks and shows that digitalization reduces the importance of branch networks, intensifies competition, and reallocates activity toward uninsured depositors and higher-income borrowers, with implications for funding stability and inclusion. Haendler (2022) shows that mobile technology adoption shifts deposits and small business lending from small community banks to larger digitalized banks. Koont, Santos, and Zingales (2024) and Benmelech, Yang, and Zator (2023) examine how digitization affects deposit stability and bank fragility during monetary tightening and financial stress.

We depart from this literature in several important ways. First, many existing studies examine aggregate bank behavior, deposit markets, or balance-sheet composition. We instead use granular loan-level data to study how online banks price individual loans across the borrower risk distribution and how this shapes market segmentation. Second, while prior work emphasizes the advantages of digital banking, we focus on a key limitation: online banks are more constrained in screening borrowers whose risk cannot be fully captured by hard information, which limits their ability to compete for riskier borrowers. Third, existing studies mostly emphasize demand-side differences in the use of digital channels. We complement this work by isolating the supply side. We provide causal evidence that online banks specialize in low-risk segments because their branchless, low-cost operations and fully-automated, hard-information-based screening are ill-suited to higher-risk borrowers, while traditional banks retain these riskier borrowers. We show that this generates adverse selection in traditional banks' borrower pools.

This paper also contributes to the broader literature on financial technology and credit market segmentation. A substantial body of research examines how fintech lenders and digital platforms have affected credit markets. Studies show that fintech lenders can expand credit access to underserved segments by employing alternative data sources (Di Maggio, Ratnadiwakara, and Carmichael, 2022; de Roure, Pelizzon, and Thakor, 2022;

Gopal and Schnabl, 2022; Cornelli, Frost, Gambacorta, and Jagtiani, 2022; Nam, 2023). Related work documents that differences in lending technologies lead to segmentation across credit markets, with data-enabled lenders capturing on-platform transactions and traditional banks focusing primarily on collateralized lending (Huang, 2021). The regulatory environment plays a crucial role in shaping market structure, as lighter regulatory burdens create competitive advantages for fintech lenders, which in turn influence market segmentation (Buchak, Matvos, Piskorski, and Seru, 2018; Cramer, Ghosh, Kulkarni, and Vats, 2026; de Roure, Pelizzon, and Thakor, 2022). To our knowledge, this paper is the first to jointly analyze consumer loan data from online banks, traditional banks, and fintech lending platforms, with the explicit goal of distinguishing between market expansion and business-stealing effects. While we confirm the existing literature showing that fintech lenders primarily expand credit by serving previously underserved borrowers, we highlight a distinct business-stealing effect driven by online banks, which mainly operates through cherry-picking along the borrower risk distribution.

The remainder of this paper is organized as follows: Section 2 presents a conceptual framework and theoretical predictions. Section 3 describes the available data. Section 4 focuses on our empirical tests on model predictions. Section 5 concludes.

2 Model and Empirical Predictions

In this section, we describe the theoretical framework that guides our empirical analysis. We assume a unit mass of potential borrowers. A fraction $\pi_L \in (0,1)$ are *low-risk* (type $b = L$), a fraction π_M are *medium-risk* (type $b = M$), and a fraction $\pi_H = 1-\pi_L-\pi_M$ are *high-risk* (type $b = H$). Each borrower needs one unit of funding to undertake a project. If funded, type $b \in \{L, M, H\}$ succeeds with probability θ_b and yields Y_b; otherwise the project yields 0. We assume that riskier projects have higher upside:

$$\theta_L > \theta_M > \theta_H \quad \text{and} \quad Y_H \geq Y_M \geq Y_L.$$

Borrowers are risk-neutral, protected by limited liability, and pay an application/effort cost $c \geq 0$ (borne regardless of success). The competitive outside option is normalized to 0.

There are three types of lenders: $l \in \{T, O, F\}$, where T stands for traditional banks, O for online banks, and F for fintechs. Traditional banks raise funds at cost 1 per unit (opportunity cost / deposit rate normalized to 0). Online banks and fintechs have lower costs. For online banks, lower costs reflect operational efficiencies (automated underwriting, lack of human intermediated processes, and no branch networks). For fintechs, cost advantages stem both from lighter regulatory and capital requirements and

operational efficiencies:

$$0 < \tau_F < \tau_O < 1.$$

All lenders offer a single gross repayment $(1 + r)$ due only if the project succeeds (no collateral). We assume there are enough lenders of each type that interest rates are set competitively to break even.

Screening. Lenders differ in the signals they receive about borrowers. Traditional banks can identify high-risk borrowers but cannot distinguish between medium- and low-risk borrowers. Online banks can identify low-risk borrowers but cannot distinguish between medium- and high-risk borrowers. Fintechs have better technology (i.e. AI/ML-based algorithmic underwriting) that leads them to increase the success probability for high risk borrowers compared to online and traditional banks.

These assumptions reflect differences in screening technologies. Online banks rely on automated underwriting using hard information, which is informative for identifying low-risk borrowers but less so at the medium/high-risk margin. Traditional banks rely on relationship lending and soft information, which is most valuable for identifying high-risk borrowers, and legacy data systems limit their capacity for efficient hard-information screening at scale.

Timing. Lenders simultaneously post interest rates. Borrowers observe posted rates and decide whether to apply. Projects realize, and repayments are made if projects succeed.

Borrower participation. Given interest rate r, a type-b borrower's expected payoff is

$$U_b(r) = \theta_b\big(Y_b - (1 + r)\big) - c.$$

Type b participates iff $U_b(r) \geq 0$, i.e.

$$r \leq \ r_b \equiv Y_b - 1 - \frac{c}{\theta_b}.$$

We impose the sorting assumption

$$r_H > \ r_M > r_L, \tag{1}$$

which ensures that as r rises, low-risk borrowers exit first, followed by medium-risk borrowers, and only high-risk borrowers remain.

Lender decisions. Under perfect competition, any offered contract must break even. If a set B of borrower types is served at a common gross repayment $1 + r$, the lender's

expected revenue per borrower is

$$\bar{\theta}_B(1+r), \qquad \text{where } \bar{\theta}_B \equiv \frac{\sum_{b\in B}\pi_b\theta_b}{\sum_{b\in B}\pi_b}.$$

Break-even requires

$$\bar{\theta}_B(1+r) = \begin{cases} 1 & \text{for } l = T, \\ \tau_O & \text{for } l = O, \\ \tau_F & \text{for } l = F, \end{cases}$$

which pins down the corresponding interest rate $r_l(B)$. Borrowers of type $b \in B$ accept the contract only if $r_l(B)$ does not exceed the relevant participation threshold.

Only traditional banks

A traditional bank posts a single rate to the set of borrowers it cannot distinguish within. It can (i) pool L and M at a common rate or (ii) serve only M by setting a rate that screens out L. Independently, it may decide whether to offer a separate product to H. Borrowers' break-even rates are

$$r_T(LM) = \frac{1}{\bar{\theta}_{LM}} - 1, \quad r_T(M) = \frac{1}{\theta_M} - 1, \quad r_T(H) = \frac{1}{\theta_H} - 1,$$

where $\bar{\theta}_{LM} \equiv \frac{\pi_L\theta_L+\pi_M\theta_M}{\pi_L+\pi_M}$. Since $\bar{\theta}_{LM} > \theta_M > \theta_H$, it follows that $r_T(H) > r_T(M) > r_T(LM)$.

Feasibility.

$$\begin{aligned} \text{LM pooling feasible} &\iff r_T(LM) \le r_L, \\ \text{M-only feasible} &\iff r_T(M) \le r_M, \\ \text{H-only feasible} &\iff r_T(H) \le r_H. \end{aligned}$$

Equilibrium selection. If multiple zero-profit contracts serving the same borrower type are feasible, the contract with the lowest interest rate prevails. Hence, whenever both LM-pooling and M-only contracts are feasible, LM-pooling dominates.

Result (Only L and M served). A traditional bank serves *only* L and M together (and does not serve H) if:

(i) **LM pooling is feasible:**

$$\frac{1}{\bar{\theta}'_{LM}} \le Y_L - \frac{c}{\theta'_L};$$

(ii) **H is infeasible at T:**

$$\frac{1}{\theta_H} - 1 > r_H \quad \Longleftrightarrow \quad \theta_H Y_H < 1 + c.$$

Traditional and online banks

Now introduce online banks ($l = O$), which can separate L from $\{M, H\}$. Traditional banks ($l = T$) can exclude H but cannot distinguish L from M.

Online banks' break-even rates are

$$r_O(L) = \frac{\tau_O}{\theta_L} - 1, \qquad r_O(MH) = \frac{\tau_O}{\bar{\theta}_{MH}} - 1, \qquad r_O(H) = \frac{\tau_O}{\theta_H} - 1,$$

where $\bar{\theta}_{MH} \equiv \frac{\pi_M \theta_M + \pi_H \theta_H}{\pi_M + \pi_H}$.

Cherry-picking. Suppose (i)–(ii) above hold and, in addition,

$$\frac{\tau_O}{\theta_L} - 1 \leq r_L, \quad \frac{1}{\theta_M} - 1 \leq r_M, \quad \frac{\tau_O}{\theta_H} - 1 > r_H.$$

Then the unique competitive outcome is

O serves all L at $r_O(L) = \frac{\tau_O}{\theta_L} - 1$, T serves all M at $r_T(M) = \frac{1}{\theta_M} - 1$, H is unserved.

Traditional, online, and fintech banks

Now introduce fintechs ($l = F$) that can *target high-risk borrowers* and enjoy a strictly lower regulatory cost than online banks.

Feasibility (borrower participation). Borrower participation is evaluated using the success probability induced by the contracting lender. Hence:

$$\begin{aligned} L \text{ at } O \text{ feasible} \quad &\Longleftrightarrow \quad \frac{\tau_O}{\theta_L} - 1 \leq r_L, \\ M \text{ at } T \text{ feasible} \quad &\Longleftrightarrow \quad \frac{1}{\theta_M} - 1 \leq r_M, \\ H \text{ at } F \text{ feasible} \quad &\Longleftrightarrow \quad \frac{\tau_F}{\theta_H} - 1 \leq r_H. \end{aligned}$$

We maintain that H is infeasible for T and O:

$$\frac{1}{\theta_H} - 1 > r_H \quad \text{and} \quad \frac{\tau_O}{\theta_H} - 1 > r_H,$$

so neither T nor O can profitably serve H absent fintech entry.

Equilibrium segmentation with fintech entry. Suppose the feasibility and infeasibility conditions above hold. Then the unique competitive equilibrium features full segmentation:

$$\begin{aligned} O \text{ serves all } L \text{ at} \quad & r_O(L) = \frac{\tau_O}{\theta_L} - 1, \\ T \text{ serves all } M \text{ at} \quad & r_T(M) = \frac{1}{\theta_M} - 1, \\ F \text{ serves all } H \text{ at} \quad & r_F(H) = \frac{\tau_F}{\theta_H} - 1. \end{aligned}$$

- L **prefers** O **to** T**.** Any attempt by T to retain L requires pooling $\{L, M\}$ at $r_T(LM) = \frac{1}{\bar{\theta}_{LM}} - 1$, which exceeds $r_O(L)$ because $\tau_O < 1$ and $\theta_L > \bar{\theta}_{LM}$.
- M **prefers** T **to** O**.** O cannot target M alone and must price the pool $\{M, H\}$ at $r_O(MH) = \frac{\tau_O}{\bar{\theta}_{MH}} - 1$, where $\bar{\theta}_{MH} < \theta_M$, implying $r_O(MH) > r_T(M)$.
- H **is served only by** F**.** T would require at least $r = \frac{1}{\theta_H} - 1 > r_H$, while O would require $r = \frac{\tau_O}{\theta_H} - 1 > r_H$. Fintechs can profitably serve H due to their lower regulatory cost τ_F.

2.1 Theory Predictions

Three testable predictions are derived from the model.

Prediction 1: *Market segmentation across lender types.*

In equilibrium, lending markets exhibit segmentation by borrower risk. Online banks concentrate on low-risk borrowers, traditional banks primarily serve borrowers in the intermediate risk range, and fintechs specialize in higher-risk segments of the borrower distribution.

Prediction 2: *Comparison of interest rates across online and traditional banks.*

Online banks offer lower interest rates than traditional banks for low-risk borrowers, while traditional banks offer lower interest rates for medium-risk borrowers. Extending the model from discrete to continuous borrower risk implies the existence of a cutoff risk level at which the ranking of interest rates reverses: below this threshold, online banks charge lower rates; above it, traditional banks do. This generates a crossover point in the interest-rate–risk profile across lender types.

Prediction 3: *Effect of online bank development on traditional banks' interest rates.*

The development of online banks worsens the risk composition of traditional banks' borrower pools. By disproportionately attracting low-risk borrowers, online banks leave traditional banks with a relatively riskier applicant pool than in the absence of online competition. As a result, the interest rates faced by medium-risk borrowers at traditional banks increase.

3 Data

This paper adopts the definitions of online banks as presented by Abrams (2019) and Erel, Liebersohn, Yannelis, and Earnest (2023). Online banks, or online direct banks, are depository institutions without physical branches. Different from recent studies that focus on the adoption of digital platforms by traditional banks (Koont, Santos, and Zingales, 2024; Koont, 2023), this paper focuses explicitly on digital-only banks that operate without any physical branch networks and underwrite loans entirely via web without branch visits, telephone sales, or human intermediation in the origination process.

The direct bank model—licensed depository institutions operating without physical branches—has a long history in Germany and internationally (e.g., First Direct in the UK, 1989; Ally Bank in the US), and has grown substantially as branch networks contract and digital infrastructure expands. In Germany, ING-DiBa now serves over nine million retail customers, making it the country's third-largest retail bank by customer base. The online banks in our sample are established, fully licensed depository institutions with decades of consumer lending on their balance sheets. Their cost advantage derives from an organizational choice to avoid branch infrastructure. Our sample does not include recent neobank entrants such as N26 or Revolut, which is unlikely to affect our analysis since these institutions remain primarily focused on payments and deposits, with limited consumer lending activity on their balance sheets.

Fintech lenders also utilize technology to provide credit services online, but they differ fundamentally from online banks because they typically do not hold banking charters and are not subject to bank regulation. Instead, they partner with licensed banks to carry out the lending business. Although some Fintech platforms have acquired banking licenses to lower funding costs and diversify product offerings (Vives, 2017), this paper examines explicitly those that remain non-depository institutions, thus maintaining a clear distinction from fully digital online banks.

Loan-level data. This study uses loan-level data from traditional banks, online banks, and Fintech lenders in Germany to analyze credit market segmentation. Given the limitation of accessing comprehensive loan data from all lenders directly, we collect bank loan data from the European Data Warehouse (EDW). EDW was established in 2012 as Europe's first securitization repository, designed to facilitate the collection, validation, and monitoring of loan-level performance data for asset-backed securities. Our sample covers the period from January 2019 to June 2025.

The sample includes six lenders classified into three types. *Traditional banks* are licensed depository institutions that originate loans through human-intermediated lending, such as via branch networks or telesales, etc.: HypoVereinsbank (UniCredit Bank GmbH), one of Germany's largest universal banks, Santander Consumer Bank AG, a consumer

lending specialist, and BNP Paribas Personal Finance, the consumer lending arm of BNP Paribas in Germany. *Online banks* are branchless depository institutions that originate loans entirely through digital channels without human intermediation in the credit decision: ING-DiBa AG, Germany's largest online bank and the country's third-largest retail bank by customer base, with over nine million customers and approximately EUR 200 billion in total assets as of 2024,[1] and South-West Credit Bank, a direct bank specializing in consumer installment loans since 1959. *Fintech* includes Auxmoney, one of the largest in continental Europe and Germany's largest peer-to-peer lending platform, operating as a non-depository institution.

Several traditional banks in our sample are German subsidiaries of international banking groups. All are licensed credit institutions in Germany, supervised by BaFin, and originate loans to German residents under German consumer credit law. What matters for our analysis is the lending process: these institutions employ human-intermediated underwriting—via branches or telesales—that combines hard and soft information. Loan officers interact with borrowers, assess documentation, and exercise discretion in ways that fully automated digital-only lenders cannot.

Securitization regulation and representativeness. While securitized loans provide highly granular data, a natural question is whether they are representative of lenders' overall loan portfolios. The EU Securitisation Regulation (Regulation (EU) 2017/2402),[2] in force since January 2019, directly addresses this concern through three provisions. First, Article 9 requires that originators apply the same credit-granting criteria to loans that are subsequently securitized as to loans they retain on their balance sheets, directly prohibiting weaker origination standards for securitized pools. Second, if originators apply specific selection criteria to determine which loans from their portfolio enter a securitization, these criteria and their rationale must be disclosed to investors. Originators may select loans by vintage, region, or other observable characteristics, but they cannot selectively transfer higher- or lower-quality loans based on private information without disclosure. Third, Article 6 imposes a 5% risk retention requirement, ensuring that originators retain economic exposure to the securitized pool. Together, these provisions—same underwriting standards, disclosed selection criteria, and retained economic exposure—support the comparability of securitized and retained loans for our analysis. Consistent with this, Billio, Dufour, Segato, and Varotto (2023) document the absence of cherry-picking in mortgage loan securitizations following the introduction of the regulation.

To further assess whether securitized loans represent lenders' overall loan portfolios, we compare securitized and unsecuritized loans for a specific lender that provided internal data. Access to the complete loan-level dataset of Auxmoney,[3] the largest German fintech

[1] https://www.ing.de/ueber-uns/unternehmen/investor-relations/investor-relations-en/
[2] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017R2402
[3] https://www.auxmoney.com/, accessed January 2026.

lender, enables this validation. The dataset covers the period from January 2018 to May 2022 and includes both securitized and unsecuritized loans. This comprehensive coverage allows us to directly test whether the fintech's securitized loans differ systematically from those that remain on its balance sheet.

We report this comparison in Table A.1. The analysis of securitized and unsecuritized loans issued after 2019 reveals a high degree of comparability between the two groups. Across key characteristics, including loan age, interest rate, credit score category, loan amount, and loan maturity, we observe only minimal differences. These findings support the representativeness of securitized loans within lenders' overall loan portfolios.

Historical branch-level location data. We measure bank branch density at the NUTS-3 district level using data from OpenStreetMap (OSM), an open-source geographic database that provides freely available geodata with standardized metadata tags for points of interest. OSM records the location and type of commercial establishments, including financial institutions, through a structured tagging system. We extract all geo-referenced points of interest within Germany tagged as bank, which captures physical bank branch locations across all bannks. Each extracted branch location is assigned to a NUTS-3 district based on its geographic coordinates using spatial joining with official NUTS boundary shapefiles from Eurostat's GISCO geographical information system.[4]

District-level economic controls. We supplement the branch density data with pre-sample district-level economic characteristics at the NUTS-3 level, sourced from Eurostat's regional statistics, to control for local conditions that may correlate with both historical branch networks and lending outcomes. These include GDP, population density (computed as total population divided by district land area in square kilometers), and the employment rate (defined as the number of employed persons aged 15 to 64 as a share of the working-age population).

Household-level survey data. To examine which borrowers select into online banks and which face rejection, we use the Panel on Household Finances (PHF), a representative household survey conducted by the Deutsche Bundesbank as part of the Eurosystem Household Finance and Consumption Survey (HFCS). We use waves 2 through 5 (2014, 2017, 2021, and 2023), which include questions on the household's main bank and its type. The PHF collects detailed information on household balance sheets, income, credit relationships, and banking behavior, including whether households bank with an online or traditional institution and whether they have been denied credit. These data allow us to characterize the demand side of market segmentation—identifying household characteristics associated with online bank—complementing the supply-side evidence from

[4] https://gisco-services.ec.europa.eu/tercet/flat-files

loan-level data.

3.1 Descriptive statistics

Table 1 provides descriptive statistics of loan-level data for traditional banks, online banks, and fintech lenders. The statistics reveal distinct patterns in the characteristics of the loans they offer.

[Table 1]

Online banks issue loans with the longest maturities on average. The mean loan duration at online banks is 78 months, compared with 74 months at traditional banks and 58 months at fintech lenders. Interest rates exhibit the opposite ranking: fintechs charge the highest average annual interest rates (11.4%), followed by traditional banks (6.8%), and online banks (4.6%). Notably, online banks also exhibit the lowest dispersion in interest rates (standard deviation of 1.5 percentage points), compared with 2.7 for traditional banks and 4.4 for fintechs, suggesting a more homogeneous borrower pool.

Loan amounts also differ markedly across lender types. Online banks extend the largest loans on average, with a mean (mediam) loan amount of EUR 26,600 (EUR 22,000). Traditional banks follow with a mean (median) loan size of EUR 21,084 (EUR 13,789), while fintech lenders originate substantially smaller loans, with a mean (median) amount of EUR 8,269 (EUR 6,000).

Online banks serve borrowers with the highest average income (EUR 36,742), suggesting a comparatively stronger financial profile. Fintech borrowers have an intermediate average income (EUR 31,215), while borrowers at traditional banks exhibit the lowest average income among the three groups (EUR 22,696).

Default rates confirm these risk patterns. Online banks exhibit the lowest default rate (1%), followed by traditional banks (3%), and fintechs (6%). The lower variability in both interest rates and default rates at online banks is consistent with their concentration in a narrow, low-risk market segment. Loan maturity patterns also align with the well-established negative relationship between loan maturity and credit risk, whereby riskier borrowers typically receive shorter-term loans. Taken together, these patterns provide suggestive evidence that online banks serve the lowest-risk borrowers, traditional banks serve an intermediate-risk segment, and fintechs concentrate on higher-risk borrowers.

4 Empirical Analysis

In this section, we empirically test the hypotheses developed from the conceptual framework in Section 2.

4.1 Market segmentation across lender types

Our model predicts that in equilibrium, lending markets exhibit segmentation by borrower risk where online banks concentrate on low-risk borrowers, traditional banks primarily serve borrowers in the intermediate risk range, and fintechs specialize in higher-risk segments of the borrower distribution. To test this prediction, we require a measure of borrower risk.

We proxy for borrower risk using an indicator for loan default, defined as a loan becoming 90 days past due. To obtain an ex ante measure of borrower risk, we predict default using observable borrower and loan characteristics at origination. Specifically, we estimate the following probit model of loan default:

$$\begin{aligned}\Pr(Default_i = 1) = \Phi(&\beta_1 \ln(Income_i) + \beta_2 \ln(LoanAmount_i) \\ &+ \beta_3, (Income_i \times LoanAmount_i) + \beta_4 \ln(Duration_i) \\ &+ \nu_{EmploymentStatus(i)} + \nu_{Region(i)} + \nu_{OriginationYear(i)}),\end{aligned} \tag{2}$$

where Φ denotes the standard normal cumulative distribution function and i indexes loans. The specification includes, employment status, region, and origination year fixed effects, as well as log-transformed borrower income, loan amount, loan duration, and an income-loan amount interaction as predictors of default. We include the income-loan amount interaction to account for the fact that higher-income borrowers typically borrow larger amounts. Controlling for this interaction allows us to separately identify the effects of income and loan size on default risk, rather than conflating them.

We estimate this model using loans originated through 2023, as more recent loans have not had sufficient time to mature and realize potential defaults. Including loans from 2024 and 2025 in the estimation would mechanically bias default rates downward due to right-censoring. We use the estimated coefficients to predict default probabilities for all loans in our sample, including those originated in 2024 and 2025.

This measure captures variation in default risk based solely on hard information observable to lenders at origination. While hard information does not perfectly capture the true underlying risk, our approach assumes that observable characteristics are correlated with borrower risk, that is, borrowers with better observables are lower risk on average.

The full probit regression results (marginal effect) are presented in Column (1) in Table A.2. All the coefficients of the demographics are significant and have the expected sign. The model achieves an AUC of 0.6559, indicating moderate discriminatory power in ranking borrower default risk (Figure A.2).

This model captures variation in default risk based solely on hard information observable to lenders at origination, and is unconditional on lender type and screening technology. However, even among borrowers with identical observable characteristics, default probabilities may differ across lenders due to (i) supply-side selection (lenders

employ different screening technologies with different information sets), (ii) demand-side selection (borrowers sort based on preferences or private information), or (iii) lender type causally affects repayment through differences in rates or servicing.

To test whether default rates differ systematically across lender types beyond what observable borrower characteristics can explain, we include a lender type indicator variable in our probit specification:

$$\begin{aligned}\Pr(Default_i = 1) = \Phi(&\beta_1 \ln(Income_i) + \beta_2 \ln(LoanAmount_i) \\ &+ \beta_3, (Income_i \times LoanAmount_i) + \beta_4 \ln(Duration_i) \\ &+ \boldsymbol{\nu_{Lendertype(i)}} + \nu_{EmploymentStatus(i)} + \nu_{Region(i)} + \nu_{OriginationYear(i)}),\end{aligned} \tag{3}$$

where $\nu_{Lendertype(i)}$ is an indicator variable for lender type (traditional bank, online bank, or fintech) where traditional bank is the omitted category.

As before, the probit marginal effects are reported in Column (2) in Table A.2. The analysis shows that the coefficient on the lender type indicator is statistically significant, and the coefficients for the demographics change, even though the signs remain in line with the previous one. The coefficient on *OnlineBank* is -0.0233 and *Fintech* is 0.0557 and are significant at the 99% level. This indicates that even among borrowers with identical observable characteristics, default probabilities differ systematically across lender types. The model achieves an AUC of 0.7229, a noticable improvement from 0.6559 without lender type, indicating that lender type captures risk-relevant information beyond observable borrower characteristics (Figure A.2).

Our analysis allows us to distinguish two sources of risk differences across lender types: (i) differences in borrower demographics (hard information), and (ii) residual differences in default probabilities among borrowers with identical observable characteristics. To examine whether lenders serve borrowers from different parts of the risk distribution, we compare the distribution of predicted default probabilities (*RiskScore*) from the two models above. Figure 3 plots the distribution of *RiskScore* for loans originated by traditional banks (blue), online banks (green), and fintech (orange). Panel A excludes lender type from the estimation in Equation 2, Panel B includes it in Equation 3.

[Figure 3]

In Panel A, the overall distribution of *RiskScore* has a mean of 3.07% (SD = 2.1%), ranging from 0.2% to 17.8%. Disaggregating by lender type, online banks have a mean *RiskScore* of 1.04% (SD = 1.29%), traditional banks 4.01% (SD = 1.94%), and fintech 3.99% (SD = 1.78%). Based on observables alone, online banks serve a distinctly lower-risk pool, while traditional banks and fintechs serve borrowers with similar risk profiles.

This is consistent with online banks' reliance on hard-information screening—they target borrowers who are easily identifiable as low-risk based on observable characteristics. Traditional banks and fintech, in contrast, show substantial overlap, suggesting that observable characteristics alone do not clearly distinguish their borrower pools.

Panel B, which includes lender type indicators, reveals sharper segmentation across all three lender types. Online banks concentrate almost entirely below 2% *RiskScore*, traditional banks span the middle range, and fintech serves the highest-risk borrowers. The overall distribution is more dispersed, with a mean of 3.9% (SD = 3.1%). Online banks have a mean *RiskScore* of 0.48% (SD = 0.25%), traditional banks 3.50% (SD = 1.46%), and fintech 7.16% (SD = 2.16%).

The difference between panels indicates that lender type carries substantial information about borrower risk beyond observables. While online banks already differ from traditional banks on observables alone, this segmentation becomes even more pronounced with lender type indicators. Traditional banks and fintech largely overlap in Panel A but diverge sharply in Panel B, suggesting that observable characteristics alone cannot distinguish their borrower pools—lender type reveals the underlying risk differences.

To shed light on what drives this segmentation, we draw on the German Panel on Household Finances (PHF), a representative household survey conducted by the Bundesbank that records household main bank type—online or traditional—and credit application outcomes, including rejections and re-application success, along with demographics and assets and liabilities. Table 2 reports estimates from regressions of online bank adoption on household characteristics. Higher-income households are more likely to use an online bank as their primary institution. Younger households show higher adoption. Importantly, education exhibits a clear gradient, with adoption increasing monotonically from vocational training through bachelor's, master's, and PhD degrees. These patterns confirm that online bank customers tend to have characteristics positively associated with creditworthiness, consistent with demand-side sorting where more financially sophisticated and tech savvy consumers gravitate toward online banks.

[Table 2 and 3]

However, Table 3 reveals that households whose primary bank is an online bank are approximately 60% more likely to have experienced credit rejection relative to traditional bank customers, whose baseline rejection rate is approximately 7%. This holds after controlling not only for demographics but also for indicators of credit behavior—having unpaid bills and using overdraft facilities—both of which are strong predictors of rejection. Higher income and higher education predict lower rejection probability, and these are precisely the characteristics associated with online bank adoption. Yet despite their favorable demographic and credit profiles, online bank customers face substantially higher rejection rates. This pattern provides suggestive evidence that online banks apply

stringent screening even among their positively selected applicant pool, consistent with supply-side selection playing a meaningful role beyond demand-side sorting alone.

Taken together, these findings provide evidence of risk-based market segmentation. This empirical evidence supports Prediction 1.

4.2 Comparison of interest rates across online and traditional banks.

Our model predicts that online banks offer more competitive interest rates for low-risk borrowers, whereas traditional banks charge lower rates for borrowers with intermediate risk levels.

We examine how interest rates vary across lender types as a function of borrower risk. The fitted probabilities from this model, $\Pr(\widehat{Default_i})$, serve as our model-based risk scores, *RiskScore*, for the investigation of the differences in loan interest rates across online banks and traditional banks. Given that the focus of the paper is on online banks vs traditional banks, in this section we concentrate on testing prediction 1 i.e. on the comparison between online and traditional banks interest rates. For completeness, in section xx we investigate also fintech lender interest rates.

Focusing on loans originated by traditional and online banks, we estimate the following OLS specification:

$$\begin{aligned} r_i = {} & \beta_1\, OnlineBank_i + \beta_2\, RiskScore_i + \beta_3\, (OnlineBank_i \times RiskScore_i) \\ & + \beta_4 \ln(Income_i) + \beta_5 \ln(LoanAmount_i) + \beta_6, (Income_i \times LoanAmount_i) \\ & + \beta_7 \ln(Duration_i) + \nu_{EmploymentStatus(i)} + \nu_{Region(i)} + \nu_{OriginationYear(i)} + \varepsilon_i. \end{aligned} \tag{4}$$

Here, r_i denotes the interest rate on loan i. $OnlineBank_i$ is an indicator equal to one if the loan is originated by an online bank, and zero otherwise. $RiskScore_i$ measures the predicted probability of default constructed from our probit model. We cluster standard errors at the region-year level.

The coefficients of interest are β_1, which captures the interest rate differential between online and traditional banks for borrowers with zero predicted risk, β_2, which measures how interest rates at traditional banks vary with borrower risk, and β_3, which captures the differential sensitivity of interest rates to risk at online banks relative to traditional banks. The interaction term allows the relationship between borrower risk and interest rates to differ systematically across lender types.

We expect $\beta_2 > 0$, reflecting the positive relationship between borrower risk and interest rates. If online banks possess a competitive advantage for low-risk borrowers that diminishes as borrower risk increases, we further expect $\beta_1 < 0$, indicating lower interest rates for zero-risk borrowers at online banks, and $\beta_3 > 0$, implying that this

advantage narrows as borrower risk rises.

Table 4 reports the results from estimating Equation 4, which relates interest rates to lender type and borrower risk. Column (1) reports OLS estimates and column (2) reports fixed effects estimates. The results reveal substantial heterogeneity in interest rate differentials across the risk distribution. At zero predicted risk, online banks offer interest rates that are approximately 3.8 percentage points lower than those charged by traditional banks ($\beta_1 = -3.8$). Consistent with expectations, interest rates increase with borrower risk, as captured by the positive and statistically significant coefficient on the risk score ($\beta_2 = 20.2$).

[Table 4]

However, the positive and highly significant interaction term ($\beta_3 = 116.7$) indicates that online banks' pricing advantage diminishes sharply as borrower risk increases, implying that traditional banks become more competitive for higher-risk borrowers.

Overall, these findings support the model's prediction of a crossover in interest rate competitiveness. Online banks offer lower rates to low-risk borrowers, while traditional banks price risk more favorably for borrowers with higher risk. The estimated coefficients imply a well-defined crossover point beyond which traditional banks would offer lower interest rates than online banks. Quantitatively, this crossover occurs at a predicted risk score of approximately 3.2% (computed as $|\beta_1|/\beta_3 = 3.778/116.652 = 0.027$). This pattern remains robust across both the OLS specification (column 1) and the fixed effects specification (column 2).

[Figure 4]

Figure 4 visualizes this crossover pattern by plotting predicted interest rates from the regression reported in column (1) of Table 4. The figure shows how interest rates vary with *RiskScore* for online and traditional banks while holding all other covariates constant. The steeper slope for online banks highlights the faster increase in interest rates with borrower risk, which erodes their pricing advantage as risk rises. The two profiles intersect at a predicted risk of approximately 3.2%, illustrating the crossover point implied by the regression coefficients.

Taken together, the regression results and the graphical evidence provide empirical support for Prediction 2.

4.2.1 IV evidence: Supply-driven online bank cherry picking and rate advantages

Our conceptual framework highlights two mechanisms through which online bank development may affect pricing and market segmentation in consumer credit markets. First,

online banks, together with fintech, benefit from a *cost advantage* due to lower operational expenses associated with digital-only business models. Second, lenders differ in their *screening technologies*: online banks rely primarily on rule-based screening using hard information, whereas traditional banks can deploy more information-intensive screening methods that are particularly valuable for borrowers with intermediate risk profiles.

We begin by providing descriptive evidence on the cost advantage of online banks. Figure 6 plots operating costs scaled by total assets across lender types, while Figure 7 reports operating costs relative to income. Both figures show that online banks operate with substantially lower cost ratios than traditional banks throughout the sample period. These patterns are consistent with the notion that digital-only banks benefit from lower fixed and variable costs, allowing them to offer more competitive pricing.

[Figure 6 and 7]

While these figures document a clear cost advantage for online banks, they do not by themselves speak to differences in screening technologies. In particular, lower costs alone cannot explain why online banks concentrate sharply in low-risk segments or why their pricing advantage diminishes rapidly with borrower risk. We need an analysis that disentangles the roles of screening by different lenders from those of demand. We therefore implement an instrumental variables strategy that exploits exogenous variation in online bank usage.

The endogenous regressor in our specification is *Online*, which may reflect borrower self-selection into lending channels rather than lender screening. Because we are interested in how online bank pricing varies with borrower risk, *Online* is also interacted with borrower risk. This implies that the correlation between *Online* and the error term is likely to carry through to any interaction involving *Online* (Wooldridge, 2010). Therefore, both the endogenous regressor and its interaction term have to be instrumented. In our IV analysis, we use historical local branch density as the instrument for *Online*, and interact branch density with the risk measures to instrument $Online \times Risk$. This follows the standard approach of constructing instruments for interaction terms by interacting the excluded instrument with the interacted variable (Wooldridge, 2010).

The IV estimates allow us to examine how interest rates change when borrowers are pushed toward online banks by local branch scarcity rather than by their own selection decisions. If the pricing differences reflect supply-side screening as predicted by our model, we should continue to observe lower interest rates for low-risk borrowers who are exogenously induced into online banks, while mid-risk borrowers do not receive a comparable rate advantage.

By contrast, if the observed pattern were mostly driven by demand-side sorting—where low-risk borrowers choose online banks and the lower observed rates simply reflect their better underlying credit quality—then moving borrowers into online banks through this

external cost shifter would not reproduce the same pricing pattern. In other words, borrowers who switch to online banks because of branch scarcity would not experience systematically lower rates in the low-risk group relative to the mid-risk group.

Both in our conceptual framework and in the data, online banks are largely absent from the high-risk segment, and the relevant margin of competition lies between low- and mid-risk borrowers. To align the empirical specification with this screening margin, we discretize the lender-neutral *RiskScore* constructed in Equation 2 into terciles and estimate segment-specific IV effects within the low- and mid-risk groups. This *RiskScore* is a predicted default probability constructed using only observable borrower and loan characteristics and excluding lendertype indicators. As a result, borrowers are classified into risk segments based on ex ante observables that are comparable across lending channels.

Let $s \in \{L, M\}$ index the low- and mid-risk segments. We construct segment-specific instruments as

$$Z_{is} = BranchDensity2017_m \times I\{i \in s\}, \tag{5}$$

where i indexes loans, m indexes districts (NUTS-3), and $BranchDensity2017_m$ denotes historical bank branch density within district m (Figure A.3).

The first-stage equation is

$$Online_{is} = \pi_s Z_{is} + \mathbf{X}_i'\boldsymbol{\gamma} + \mu_f + \delta_t + \varepsilon_{is} \tag{6}$$

where $\mathbf{X}_i$ includes controls used in Equation 8, along with risk-bin indicators, pre-sample district-level controls (GDP, population density, and employment rate). μ_f and δ_t denote federal-state, origination-year fixed effects. Intuitively, each first-stage equation tests whether branch density predicts online bank usage within a given risk segment. Although the model is estimated on the pooled sample, identification of the segment-specific coefficient π_s comes solely from within-segment variation. For observations outside segment s, both the endogenous variable and the instrument are set to zero. However, these observations remain in the regression because the first-stage equations are estimated jointly within a unified 2SLS framework for estimating the overall variance structure.

The second stage is:

$$r_i = \sum_{s \in \{L,M\}} \beta_s \widehat{Online}_{is} + \mathbf{X}_i'\boldsymbol{\Gamma} + \mu_f + \delta_t + u_i. \tag{7}$$

where r denotes the interest rate. The coefficients β_s capture the change in interest rates for borrowers in risk segment s when they are exogenously shifted into online banks. In line with model prediction 2, we expect low-risk borrowers to receive lower rates ($\beta_L < 0$), while mid-risk borrowers do not receive a comparable rate advantage $\beta_M \approx 0$.

The identifying assumption is that historical branch density affects loan rates primarily through its influence on costs of accessing physical branches—shifting some low- and

mid-risk borrowers from traditional onto online banks—rather than directly affecting the interest rate. However, several channels could threaten the exclusion restriction.

First, historical branch density may reflect persistent local banking market structure. Districts that had fewer branches in 2017 may still have less competitive traditional banking markets today, allowing incumbent banks to charge higher rates regardless of online bank entry. If this is the case, what appears as lower online bank rates relative to traditional banks would partly reflect inflated traditional bank pricing due to local market power, inflating our IV estimates.

Second, the historical branch network did not arise randomly—it reflects decades of bank location decisions that respond to local economic conditions, and demographics. If those local characteristics are slow-moving, and also correlated with unobserved components of borrower quality in our sample period, they can directly affect default rates and pricing. Thus, the instrument partly would capture risk differences rather than channel switching due to branch scarcity.

To mitigate such confounding, we saturate our IV setup with fixed effects at the NUTS-1 (federal-state) level, the level at which key banking regulation and institutional arrangements are determined in Germany, by loan-origination year, and by employment status group, while clustering standard errors at the NUTS-3 (district) level. We also include pre-sample district-level economic controls—GDP, population density, and employment rate, to absorb the structural and market-condition variation that is likely correlated with historical branch-network density.

To further address the concerns, we also conduct falsification tests to assess whether historical branch density directly predicts interest rates and default outcomes for traditional bank loans conditional on our full set of controls. Neither test yields a significant effect, lending support to the exclusion restriction.

[Table 5]

Table 5 presents the IV estimation results. Panel A reports the first-stage regressions. Branch density significantly predicts online bank usage. *BranchDensity2017* is negative and statistically significant for low risk, -0.078, $t = -4.10$ in Column (1), and for mid risk, -0.050, $t = -2.82$ in Column (2). The negative coefficients imply that borrowers in districts with fewer traditional bank branches are more likely to obtain loans from online banks. The Sanderson–Windmeijer first-stage F-statistics for low risk (mid risk) is 13.19 (14.10) which exceeds conventional thresholds of 10 (Staiger and Stock, 1997), indicating that the instruments are sufficiently strong for each endogenous variable individually.

The relative magnitude of the first-stage coefficients is informative. The instrument is roughly 35% weaker for mid-risk borrowers. This asymmetry is difficult to reconcile with a purely demand-driven account of channel choice. Branch density operates through

transaction costs of accessing traditional banks, a cost that does not depend on a borrower's credit risk. If demand alone were driving channel choice, reductions in branch access would be expected to shift both low- and mid-risk borrowers toward online banks with comparable strength. The weaker first stage for mid-risk borrowers instead suggests a supply-side constraint. Even when branches are scarce and switching costs fall, these borrowers cannot move to online banks at the same rate because online banks' screening either rejects their applications or offers unattractive terms.

Column (3) of Table 5 reports the second-stage 2SLS results, where interest rates are regressed on the instrumented measures of online bank usage within each risk segment. The coefficient on $\widehat{Online}_{Lowrisk}$ is -6.33 percentage points and highly statistically significant. This implies that low-risk borrowers who are exogenously induced to obtain loans from online banks pay substantially lower interest rates than comparable borrowers at traditional banks. In contrast, the coefficient on $\widehat{Online}_{Midrisk}$ is economically small and statistically insignificant, indicating that the online rate advantage does not extend to mid-risk borrowers. These results confirm that the crossover pattern documented in our rate cross-over analysis in Equation (4) is not purely due to self-selection but due to supply-side screening.

The Sanderson–Windmeijer first-stage F-statistics of 13.19 and 14.10 confirm that each instrument is individually strong. The joint Kleibergen–Paap F-statistic is 6.49, modestly below the 10% Stock–Yogo critical value of 7.03, reflecting the shared underlying variation in interaction-based instruments. However, the Anderson–Rubin test (F=8.52, p<0.001) confirms the joint significance of the endogenous regressors under weak-instrument-robust inference. The conclusion—a large rate advantage for low-risk borrowers that disappears for mid-risk borrowers—is consistent across OLS and IV specifications.

Robustness. Our main IV specification uses risk bins rather than the continuous risk score. Bins allow for flexible, nonparametric heterogeneity in the online bank effect across risk segments without imposing that the rate differential varies linearly with credit risk. They also produce directly interpretable coefficients—the rate effect of online banking within each segment—rather than requiring translation through marginal effects. As a robustness check, we re-estimate the IV using the same continuous specification as the OLS in Equation (4), instrumenting both *Online* and *Online* × *Risk* with *BranchDensity2017* and *BranchDensity2017* × *Risk*. The results, reported in Table A.3, are consistent: the coefficient on $\widehat{Online}$ is -7.84 ($p < 0.01$) and $\widehat{Online} \times Risk$ is positive and significant, yielding an implied crossover at approximately 3.0% predicted default probability—close to the 3.2% from OLS. First-stage diagnostics are similar, with Sanderson–Windmeijer F-statistics of 14.79 and 18.37, a joint Kleibergen–Paap F-statistic of 6.94, and the Anderson–Rubin test rejecting at $p < 0.001$.

Falsification tests. The IV estimates are stable across specifications, but depend on the assumption that branch density affects interest rates only through online bank channel choice. We test this exclusion restriction directly.

[Table 6]

Table 6 reports falsification tests for the exclusion restriction of our instrumental variables strategy. The sample is restricted to traditional bank loans only. Column (1) tests whether historical branch density directly affects traditional bank interest rates. If branch density operated through local banking competition rather than through online bank channel switching, we would expect a negative coefficient: fewer branches imply less competition, leading to higher rates. The estimated coefficient is statistically insignificant, ruling out the competition channel as a threat to identification.[5]

Column (2) tests whether historical branch density predicts default among traditional bank borrowers. A significant effect would suggest that branch density correlates with unobserved borrower quality, violating the exclusion restriction. The coefficient is economically zero and statistically insignificant, indicating that branch density does not capture unobserved risk characteristics conditional on our controls. Together, these tests support the validity of branch density as an instrument that affects interest rates only through its effect on online bank channel choice.

4.3 Effect of online bank development on traditional banks' interest rates.

Next, we test whether traditional banks face increasingly riskier borrower pools as online banks disproportionately attract low-risk borrowers. This prediction has two components. First, we examine whether the risk composition of borrowers served by traditional banks shifts toward higher risk as online banks expand. Second, we investigate whether traditional banks respond by charging higher interest rates over time, conditional on observable borrower risk characteristics.

[Figure 5]

Figure 5 illustrates the evolution of *RiskScore* distributions by lender type from 2019 to 2025. Across all years, online banks consistently concentrate in the lowest-risk segments of the market, with the majority of their lending directed toward borrowers with risk scores below 2%. In contrast, the borrower risk distribution at traditional banks shifts

[5]The insignificant yet positive sign is consistent with the adverse selection mechanism documented by Beyhaghi, Fracassi, and Weitzner, 2025, whereby greater bank presence increases the likelihood that riskier borrowers obtain credit. Even if this channel were operative but too weak to detect, the resulting bias would attenuate our IV estimates toward zero, making our findings conservative.

over time: the left tail progressively thins, indicating a declining presence of low-risk borrowers in traditional banks' portfolios.

To provide more direct evidence of compositional changes, we examine how the risk gap between traditional and online banks evolves over time by interacting lender type with origination year indicators. Specifically, we estimate the following specification:

$$RiskScore_i = \sum_{t=2019}^{2025} \delta_t \, Year_t + \sum_{t=2019}^{2025} \beta_t \big(TraditionalBank_i \times OriginationYear_t \big) + \varepsilon_i \quad (8)$$

Online bank is the omitted lender category. The coefficients on $TraditionalBank \times OriginationYear_t$ capture the traditional-online differential in each year. $\mathbf{X}_i$ includes log-transformed income, loan amount, and duration, an income-loan amount interaction, and fixed effects for borrower employment status and region. Online banks serve as the reference category. The coefficients β_t measure how this risk gap evolves over time.

[Table 7]

Table 7 quantifies the evolution of risk composition by lender type from 2019 to 2025. The year main effects, which capture changes in online banks' average risk scores, are small and stable across all years. This indicates that online banks consistently concentrate in the lowest-risk segments of the market throughout the sample period.

In contrast, the interaction coefficients reveal that traditional banks serve increasingly riskier borrowers over time, particularly from 2019 to 2021 when the differential rises from 2.0 to 3.2 percentage points. The slight moderation in the differential after 2022 likely coincides with the ECB's interest rate hiking cycle, during which lending standards typically tighten across the banking sector (Maddaloni and Peydró, 2011; Jiménez, Ongena, Peydró, and Saurina, 2014). However, despite this tightening cycle, the differential remains economically large, around 1.6-1.8 percentage points from 2023 onward. This persistent gap confirms that as online banks expand their operations in the lowest-risk segments, traditional banks concentrate instead on higher-risk segments where they maintain competitive advantages.

We next examine whether these compositional changes translate into higher interest rates at traditional banks by analyzing how the traditional—online interest rate differential evolves over time. If traditional banks face increasingly riskier borrower pools, they should charge higher interest rates relative to online banks, even after controlling for *RiskScore*. To test this implication, we estimate the following specification:

$$r_i = \sum_{t=2019}^{2025} \delta_t \, OriginationYear_t + \sum_{t=2019}^{2025} \beta_t \big(TraditionalBank_i \times OriginationYear_t \big) + \mathbf{X}_i' \mathbf{\Gamma} + \varepsilon_i \quad (9)$$

Online bank is the omitted lender category. The coefficients on $TraditionalBank \times OriginationYear_t$ capture the traditional-online differential in each year. $\mathbf{X}_i$ includes the same controls as in Equation 8. The coefficients of primary interest are the β_t, which capture how the interest rate differential between traditional and online banks evolves over time after conditioning on borrower risk and other observable characteristics. An increase in these coefficients over time would be consistent with traditional banks facing increasingly riskier borrower pools.

Table 8 presents the results. The interaction terms between *TraditionalBank* and year indicators reveal a substantial widening of the interest rate differential over time. In 2019, traditional banks charged interest rates approximately 209 basis points higher than online banks. This differential increases over time, reaching 455 basis points by 2025. The pattern remains robust across specifications, with estimates remaining nearly identical across both the OLS specification (column 1) and the fixed effects specification (column 2).

[Table 8]

Under an adverse selection interpretation, the growing rate differential reflects traditional banks facing increasingly riskier borrower pools over time. As online banks disproportionately attract low-risk borrowers, traditional banks retain borrowers with higher default risk. To compensate for these higher expected losses, risks that were previously pooled with safer borrowers prior to online bank entry, traditional banks charge progressively higher interest rates.

However, an alternative explanation merits consideration. The widening interest rate differential may reflect differences in the pass-through of monetary policy across lender types rather than changes in borrower composition. This period coincides with the European Central Bank's rate-hiking cycle that began in 2022. If traditional banks pass policy rate increases to borrowers more strongly than online banks, the observed widening in rates could partly capture differential monetary policy transmission rather than adverse selection.

To distinguish between these explanations, we examine how changes in the ECB policy rate pass through to loan rates across lender types. Table 9 reports the results. Traditional banks pass through approximately 84 basis points of a 100-basis-point increase in the ECB policy rate to borrower interest rates. Online banks exhibit lower pass-through–58 basis points, corresponding to 26 basis points less relative to traditional banks.

[Table 9]

Because we observe loan rates only for originated loans, the estimated pass-through potentially reflects both pricing changes and endogenous selection. In other words, lower

sensitivity may arise either because lenders smooth rates in response to funding cost shocks (market power), or because they tighten credit standards more aggressively and reduce lending to marginal borrowers when policy rates rise (selection) (Maddaloni and Peydró, 2011; Jiménez, Ongena, Peydró, and Saurina, 2014). However, the market power interpretation is difficult to reconcile with evidence that online banks offer more competitive deposit rates (Erel, Liebersohn, Yannelis, and Earnest, 2023). This suggests that alternative mechanisms, particularly borrower selection, may explain the observed differences.

To distinguish between these mechanisms, we extend the pass-through analysis by estimating a triple interaction, $PolicyRate \times OnlineBank \times RiskScore$. This specification allows pass-through to vary with borrower risk, isolating how lending rates respond to policy changes while holding risk composition constant.

[Table 10]

Table 10 shows that once borrower risk is explicitly accounted for, pass-through of policy rate changes does not differ significantly between online and traditional banks on average. This contrasts with the lower pass-through for online banks documented in the baseline specifications that abstract from risk heterogeneity. For traditional banks, pass-through increases with borrower risk, consistent with risk-based repricing when funding costs rise. In contrast, the negative and statistically significant triple interaction indicates that pass-through for online banks becomes significantly weaker at higher risk levels. This pattern suggests that, following policy rate hikes, online banks adjust primarily by tightening credit standards and rationing higher-risk borrowers rather than by repricing them more aggressively, leading to endogenous selection that attenuates observed pass-through in the online-bank sample.

Taken together, these results indicate that differential monetary policy pass-through is unlikely to be the primary driver of the widening interest rate differential between traditional and online banks. While monetary tightening can induce short-run compositional shifts—consistent with online banks tightening credit standards for higher-risk borrowers when policy rates rise—this mechanism cannot account for the persistent divergence documented over time. Once borrower risk is explicitly accounted for, average pass-through does not differ significantly across lender types, implying that monetary policy cannot mechanically generate a growing interest rate wedge at comparable risk levels. Moreover, the traditional–online interest rate differential widens both during the period when the ECB deposit facility rate was zero or negative (2020–2022) and continues to expand after the ECB began cutting policy rates in June 2024. The persistent and growing rate premium charged by traditional banks is therefore most consistent with these banks facing increasingly riskier borrower pools over time. This interpretation aligns with the compositional evidence in Table 7 and supports Prediction 3.

4.3.1 Shift-share evidence: Branch consolidation and worsening traditional bank borrower pools

The previous section documents suggestive evidence of a widening interest rate differential between traditional and online banks, consistent with deteriorating borrower pools at traditional banks. However, this time-series pattern may reflect unobserved trends correlated with both online bank growth and traditional bank outcomes. To provide causal evidence on adverse selection, we implement a shift-share design (Bartik, 1991; Borusyak, Hull, and Jaravel, 2022; Goldsmith-Pinkham, Sorkin, and Swift, 2020) that exploits differential exposure to branch network consolidation across districts.

[Figure 8]

Figure 8 illustrates the identifying variation. German banking groups have consolidated their branch networks at sharply different rates. Between 2017 and 2024, big banks—driven largely by the Postbank–Deutsche Bank restructuring—reduced their networks by approximately 68%, and regional banks by 54%. Savings banks and cooperative banks each contracted by roughly 32%, while the remaining category declined by 13%.

We combine this differential consolidation with pre-determined differences in district-level banking group composition to construct a shift-share exposure measure:

$$BranchExposure_{d,t} = \sum_{g} Share_{g,d,2017} \times \frac{Branches_{g,t} - Branches_{g,2017}}{Branches_{g,2017}}, \tag{10}$$

where g indexes banking groups, d indexes NUTS-3 districts, and t indexes years. $Share_{g,d,2017}$ is banking group g's share of branches in district d in 2017, and the second term captures the proportional shift in banking group g's national branch count between 2017 and year t. The measure captures how much branch availability in a given district is predicted to decline based on each banking group closing branches at its national rate. For example, a district that in 2017 was predominantly served by big banks—which subsequently closed 68% of their branches nationwide—receives a much more negative value than a district served primarily by savings banks, which closed 32%. As predicted branch availability declines, the cost of accessing traditional bank lending rises, pushing borrowers—particularly low-risk borrowers who are attractive to online banks—toward online lenders and worsening the residual pool at traditional banks. Figure 9 shows the geographic distribution of the measure across German districts in 2024. There is substantial cross-district variation in exposure, reflecting differences in the degree of predicted branch closure intensity, and therefore online bank exposure.

[Figure 9]

We use this shift-share measure rather than actual district-level branch closures because the latter are endogenous to local conditions. Banks may close branches in response to local economic deterioration that independently affects borrower quality and loan pricing. The shift-share construction addresses this by decomposing district-level branch losses into two components: pre-determined local banking group shares that reflect the historical structure of each district's branch network, and national-level closure rates driven by corporate restructuring decisions—such as the Deutsche Bank–Postbank integration—rather than by conditions in any individual district.

Because $BranchExposure_{d,t}$ varies across both districts and years, we can include district and year fixed effects, absorbing all time-invariant district characteristics and common time trends. The identifying assumption is that a district's initial banking group composition is uncorrelated with time-varying determinants of lending outcomes, conditional on these fixed effects (Goldsmith-Pinkham, Sorkin, and Swift, 2020).

We regress traditional bank outcomes directly on $BranchExposure_{d,t}$—a reduced-form shift-share design in which the treatment is the exposure measure itself, rather than an instrument for a separately measured endogenous variable in 2SLS (Borusyak, Hull, and Jaravel, 2025).[6]

$$Y_{i,d,t} = \alpha + \beta\, BranchExposure_{d,t} + \mathbf{X}_i'\mathbf{\Gamma} + \mu_d + \delta_t + \varepsilon_{i,d,t}, \tag{11}$$

where i indexes loans, d indexes NUTS-3 districts, and t indexes origination years. $Y_{i,d,t}$ is either *RiskScore* or *InterestRate* for traditional bank loans. μ_d and δ_t are district and year fixed effects. $\mathbf{X}_i$ includes time-varying district-level controls for GDP, population density, and employment, and—in the interest rate specification—borrower and loan characteristics. Since more negative values of $BranchExposure_{d,t}$ indicate greater exposure to branch consolidation, a negative β implies that traditional banks in more exposed districts serve riskier borrowers.

This approach is natural in our setting: the IV analysis in Section 4.2.1 already establishes that branch scarcity shifts borrowers toward online banks, and more so for low-risk borrowers. The shift-share measure captures the same channel while adding time-varying variation that allows for district and year fixed effects, absorbing all time-invariant district characteristics and common time trends that could confound the relationship between online bank expansion and traditional bank outcomes. Importantly, our data cover a sample of lenders and cannot be used to reliably measure district-level online bank market share. The reduced-form estimates capture the total effect of differential

[6]Several studies use the shift-share measure directly as the treatment variable rather than as an instrument in 2SLS; see Borusyak, Hull, and Jaravel (2025, Table 1) for a summary. For example, Xu (2022) measures countries' exposure to the 1866 London banking crisis by combining pre-determined local bank lending shares with bank-level failure indicators, and regresses export outcomes directly on this exposure measure.

exposure to branch consolidation on traditional bank outcomes, operating through the online bank expansion channel established in Section 4.2.1.

[Table 11]

Table 11 reports the results. We restrict the sample to traditional bank loans and regress borrower *RiskScore* on $BranchExposure_{d,t}$, controlling for district and year fixed effects and time-varying district-level controls. The coefficient (Column 1) is -0.017 and statistically significant ($t = -2.47$). Since more negative values of $\text{BranchExposure}_{d,t}$ indicate greater exposure to branch consolidation, this implies that traditional banks in more exposed districts serve riskier borrowers. A one-standard-deviation increase in exposure (0.072) raises the average default probability of traditional bank borrowers by 0.12 percentage points (0.072×0.017), or approximately 3.5% relative to the traditional bank mean risk score of 3.5%.

A potential threat to identification is that initial banking group composition correlates with time-varying local economic trends that independently affect borrower quality. Our district fixed effects absorb all time-invariant differences across districts, and year fixed effects absorb common national trends. However, if districts with a higher initial concentration of big banks experienced differentially worsening local conditions over time—for reasons unrelated to branch closures—the exposure measure could capture these differential trends rather than the effect of branch consolidation on lending channel choice.

To assess this concern, we conduct a placebo test by estimating the same specification on online bank loans. Online banks operate without physical branches, so their borrower pools should be unaffected by local branch closures unless the exposure measure is picking up time-varying broader local economic conditions. Column (2) in Table 11 shows that the coefficient is economically small and statistically insignificant, confirming that branch consolidation affects the composition of traditional bank borrower pools specifically, not borrower risk in general. This asymmetry is consistent with the adverse selection mechanism: as branch closures push low-risk borrowers toward online banks, traditional banks are left with a riskier residual pool, while online banks continue to screen and serve a narrow low-risk segment regardless of local branch availability.

[Table 12]

Table 12 reports the corresponding specification with interest rates as the dependent variable. The point estimate is negative but statistically significant only at the 20% level. One possible explanation is that after absorbing district and year fixed effects, the remaining within-district variation in the exposure measure may be too small relative to the variance in individual loan rates to detect the pricing response. Nonetheless, the shift-share analysis using *RiskScore* as a dependent variable delivers a clear result

on borrower composition in Table 11—districts more exposed to branch consolidation see higher *RiskScore* among traditional bank borrowers, providing direct evidence that online bank expansion generates adverse selection on traditional banks.

4.4 Fintech Lenders

Our analysis thus far has focused on the competitive dynamics between traditional and online banks. We now turn to fintech lenders, which occupy a distinct position in the consumer credit market.

Our theoretical framework predicts that the highest-risk segment of the consumer credit market is infeasible for banks to serve profitably due to regulatory capital requirements and operational constraints. Fintech lenders, operating under lighter regulatory frameworks, can profitably serve these borrowers that banks must reject. If this market segmentation holds empirically, we should observe that fintech charges higher rates than traditional banks throughout the risk distribution, with this premium growing as risk increases—reflecting the fact that fintech serves borrowers banks cannot profitably serve at any price.

Table 13 presents regression results comparing interest rates between traditional banks and fintech lenders. Fintech lenders charge a substantial rate premium of approximately 4 percentage points relative to traditional banks. This premium grows significantly with borrower risk—the interaction coefficient of 13.4 percentage points indicates that fintech's rate premium widens sharply as risk increases. Fintech rates remain consistently higher than traditional bank rates throughout the observable risk distribution and diverge further at higher risk levels.

[Table 13]

This pattern confirms that fintech lenders serve borrowers in market segments that are infeasible for traditional banks. Regulatory capital requirements, and operational costs create a threshold beyond which traditional banks cannot profitably lend (Buchak, Matvos, Piskorski, and Seru, 2018; de Roure, Pelizzon, and Thakor, 2022). Fintech lenders fill this gap (Erel and Liebersohn, 2022) by serving these higher-risk borrowers, charging premium rates that reflect both the underlying risk and the lack of bank competition in this segment. The rate differential at higher risk levels demonstrates that fintech operates where banks are effectively absent, complementing rather than competing with traditional banking.

5 Conclusion

This paper examines the impact of online banks' entry on market structure and competition in consumer lending markets. Using loan-level data from the German consumer

credit market, we provide evidence that online banks engage in cherry-picking behavior, which generates adverse selection effects on traditional banks.

We develop a simple model in which online banks benefit from lower operational costs but face limitations in screening because they rely exclusively on hard information, while traditional banks can draw on a broader set of informational inputs. These differences give rise to a reversal in interest rate rankings across borrower risk: online banks' competitive advantage is strongest for low-risk borrowers but erodes as borrower risk increases, eventually flipping the ordering of interest rates in favor of traditional banks. We derive three testable predictions from the model and evaluate them empirically.

First, we document a clear crossover in interest rate competitiveness. Online banks offer substantially lower rates for low-risk borrowers, but this advantage declines sharply with borrower risk and reverses at higher risk levels, beyond which traditional banks offer lower interest rates. Second, we find pronounced market segmentation across lender types: online banks concentrate on low-risk borrowers, traditional banks primarily serve an intermediate-risk segment, and fintech lenders target higher-risk borrowers. Third, we provide evidence consistent with adverse selection effects. The interest rate differential between traditional and online banks widens substantially over time, even after controlling for observable borrower risk and monetary policy pass-through, suggesting that traditional banks face a progressively riskier borrower pool.

Our findings highlight an important trade-off in the digital transformation of banking. While online banks reduce operational costs and intensify competition for low-risk borrowers, leading to lower interest rates and improved access for these segments, their selective focus on safer borrowers can generate cherry-picking and adverse selection effects. As online banks disproportionately attract low-risk borrowers, traditional banks are left with relatively riskier borrower pools, which can translate into higher borrowing costs or reduced credit availability for borrowers outside the low-risk segment. As a result, the benefits of increased competition and efficiency in digital banking are unevenly distributed across borrowers, with potential consequences for credit market outcomes and welfare.

These results have implications for both policy and future research. From a policy perspective, understanding how digital transformation reshapes credit market segmentation is important for evaluating financial inclusion and the distributional consequences of banking innovation. While online banks may improve pricing and access for prime borrowers, the resulting reallocation of risk across lenders may leave traditional banks serving riskier borrower pools, with potential implications for financial stability and lending standards. Future research could explore the longer-term consequences of these dynamics for credit supply, risk-taking, and bank profitability.

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Tables and Figures

Table 1: **Loan summary statistics by lender type**

Lender type	Variable	Count	Mean	Std	Min	P25	P50	P75	Max
Traditional Bank	Income	900,560	22,695.70	18,532.63	0.00	390.00	24,630.15	39,000.00	170,484.00
	Loan Duration	900,560	73.73	27.30	3.00	49.00	85.00	97.00	125.00
	Loan Amount	900,560	21,083.87	20,418.27	474.56	6,000.00	13,789.18	29,783.96	192,165.12
	Interest Rate	900,560	6.77	2.72	0.00	4.58	6.99	8.97	21.78
	Default Rate	900,560	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Online Bank	Income	449,326	36,716.01	16,737.20	3,864.00	26,280.00	32,400.00	42,216.00	170,484.00
	Loan Duration	449,326	77.65	19.12	9.00	61.00	84.00	96.00	145.00
	Loan Amount	449,326	26,594.94	16,538.78	15.00	15,000.00	22,000.00	35,000.00	115,849.08
	Interest Rate	449,326	4.59	1.54	0.99	3.12	4.79	5.74	9.56
	Default Rate	449,326	0.01	0.08	0.00	0.00	0.00	0.00	1.00
Fintech	Income	567,844	31,367.18	15,851.65	0.00	22,000.00	28,000.00	37,000.00	170,484.00
	Loan Duration	567,844	58.35	25.14	12.00	36.00	60.00	84.00	96.00
	Loan Amount	567,844	8,239.12	7,082.50	1,000.00	3,150.00	6,000.00	10,800.00	78,050.00
	Interest Rate	567,844	11.44	4.36	1.90	7.99	11.21	15.99	17.92
	Default Rate	567,844	0.05	0.22	0.00	0.00	0.00	0.00	1.00

Notes: This table shows summary statistics for loans by lender type. Data is sourced from the European Data Warehouse. The sample period is from January 2019 to June 2025. Income is winsorized at the 0.01 and 99.9 percentile. Loan duration is in months, interest rate is in percent, loan amount is in Euros, annual income is in Euros.

Table 2: **Determinants of Online Bank Adoption as a Primary Bank**

	Dep. Var = 1(*OnlineBank* User)	
	OLS	Probit (AME)
	(1)	(2)
Income (ln)	0.003**	0.004***
	(0.002)	(0.002)
Age	−0.001***	−0.001***
	(0.000)	(0.000)
Female	0.003*	0.002
	(0.002)	(0.002)
No higher−education degree (base)		
Vocational training (incl. in progress)	0.025***	0.026***
	(0.002)	(0.002)
Bachelor's degree	0.080***	0.074***
	(0.006)	(0.005)
Master's/Diploma degree	0.097***	0.095***
	(0.004)	(0.004)
PhD	0.117***	0.118***
	(0.009)	(0.009)
North (base)		
West	−0.012***	−0.012***
	(0.003)	(0.003)
South	−0.007**	−0.007**
	(0.003)	(0.003)
East	0.014***	0.016***
	(0.003)	(0.003)
Year=2010		
Year=2011	0.007**	0.008***
	(0.003)	(0.003)
Year=2014	0.010***	0.010***
	(0.003)	(0.003)
Year=2017	0.043***	0.043***
	(0.003)	(0.003)
Year=2021	0.064***	0.063***
	(0.004)	(0.004)
Year=2023	0.075***	0.075***
	(0.004)	(0.004)
Year=2024	0.055***	0.054***
	(0.007)	(0.007)
Adjusted R2	0.039	-
Obs	176,305	176,305

Notes: This table shows estimates of the probability that a respondent uses an online bank as their primary bank. The dependent variable is an indicator equal to one if the respondent reports using an online bank. The baseline probability of loan rejection for borrowers whose principal bank is a traditional bank is 6.9%, based on survey-weighted predicted probabilities. Column (1) reports estimates from a survey-weighted linear probability model, and Column (2) reports average marginal effects from a survey-weighted probit model. All regressions use calibrated survey weights from the German Panel on Household Finances (PHF) from the Bundesbank to account for unequal sampling probabilities. Standard errors are computed using Taylor linearization. Pseudo-R^2 measures rely on likelihood comparisons that are not well defined under survey−weighted estimation. Therefore, we only report them for the OLS specification. Standard errors are reported in parentheses.

Table 3: **Who Gets Credit Applications Rejected?**

	Dep. Var = 1(Have Been Rejected)	
	OLS	Probit (AME)
	(1)	(2)
Traditional bank (base)		
OnlineBank	0.045***	0.051***
	(0.010)	(0.010)
Income (ln)	−0.035***	−0.032***
	(0.005)	(0.004)
Age	−0.001***	−0.001***
	(0.000)	(0.000)
Female	−0.004	−0.003
	(0.005)	(0.005)
Has unpaid bills	0.223***	0.110***
	(0.022)	(0.009)
Uses overdraft	0.006	0.010**
	(0.006)	(0.005)
No higher−education degree (base)		
Vocational training (incl. in progress)	−0.008	−0.010
	(0.008)	(0.007)
Bachelor's degree	−0.031***	−0.033***
	(0.010)	(0.009)
Master's/Diploma degree	−0.002	−0.006
	(0.010)	(0.010)
PhD	−0.046***	−0.079***
	(0.009)	(0.007)
North (base)		
West	−0.023***	−0.025***
	(0.008)	(0.008)
South	−0.019**	−0.019**
	(0.008)	(0.008)
East	−0.017**	−0.019**
	(0.008)	(0.008)
Year=2014 (base)		
Year=2017	−0.036***	−0.034***
	(0.007)	(0.006)
Year=2021	−0.061***	−0.059***
	(0.006)	(0.006)
Year=2023	−0.034***	−0.032***
	(0.007)	(0.008)
Year=2024	−0.080***	−0.092***
	(0.006)	(0.005)
Adjusted R2	0.058	-
Obs	32,914	32,914

Notes: This table shows estimates of the probability of a credit application being rejected by a bank. The dependent variable is an indicator equal to one if the respondent reports having been rejected conditional on having applied for a loan or credit in the last three years. The baseline probability of loan rejection for borrowers whose principal bank is a traditional bank is 6.9%, based on survey-weighted predicted probabilities. Column (1) reports estimates from a survey−weighted linear probability model, and Column (2) reports average marginal effects from a survey−weighted probit model. All regressions use calibrated survey weights from the German Panel on Household Finances (PHF) to account for unequal sampling probabilities. Standard errors are computed using Taylor linearization, which accounts for unequal sampling probabilities and within-cluster correlation induced by the survey design. The question on credit rejection was introduced in the survey from 2014. Thus, earlier year data are not part of this sample. Pseudo-R^2 measures rely on likelihood comparisons that are not well defined under survey−weighted estimation. Therefore, we only report them for the OLS specification. Standard errors are reported in parentheses.

Table 4: **Interest Rate Differentials by Lender Type and Risk (Model-based risk proxy)**

	Dep. Var = Interest rate	
	(1)	(2)
OnlineBank	-3.778^{***}	-3.769^{***}
	(0.092)	(0.092)
RiskScore	20.239^{***}	20.833^{***}
	(5.009)	(5.560)
OnlineBank × *RiskScore*	116.652^{***}	117.252^{***}
	(19.136)	(20.582)
Controls	Y	Y
Region-Year FE		Y
Adjusted R2 (Within R2)	0.546	0.395
Obs	1,349,886	1,349,886

Notes: This table presents regression results of Equation (4) testing whether online banks engage in cherry-picking by offering lower interest rates primarily to low-risk borrowers. The sample includes consumer loans from January 2019 to June 2025, with traditional banks as the omitted category. The risk proxy is *RiskScore*, the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics (income, borrower employment status, region, loan amount, duration, loan purpose, origination year), ranging from 0.0% (=0 lowest risk) to 100.0% (=1 highest risk) (mean = 3.9%, SD = 3.1%, min = 0.2%, max = 17.8%). All specifications include controls for loan amount (ln), duration (ln), borrower employment status, region and origination year. Column (1) uses an OLS estimator and column (2) uses a fixed effects estimator with region-year fixed effects. Standard errors are clustered at the region-year level and reported in parentheses.

Table 5: **IV Estimates of Online Bank Interest Rates by Risk**

	(1)	(2)	(3)
Panel A. First Stage			
	$Online_{Lowrisk}$	$Online_{Midrisk}$	
BranchDensity2017	−0.078***	−0.050***	
	(0.019)	(0.018)	
Controls	Yes	Yes	
Region (State) FE	Yes	Yes	
Loan Origination Year FE	Yes	Yes	
Employment Status FE	Yes	Yes	
SW F−Stat	13.19	14.10	
Panel B. Second Stage (2SLS)			
			$InterestRate$
$\widehat{Online}_{Lowrisk}$			−6.328***
			(1.157)
$\widehat{Online}_{Midrisk}$			0.414
			(3.111)
Lowrisk			1.186***
			(0.196)
Income (ln)			−0.309**
			(0.140)
Loan Amount (ln)			−0.149***
			(0.032)
Duration (ln)			0.532***
			(0.070)
Income (ln) × Loan Amount (ln)			0.034**
			(0.016)
Population density (ln)			0.042**
			(0.017)
GDP (ln)			−0.039**
			(0.016)
Employment rate			−0.015**
			(0.006)
Region (State) FE			Yes
Loan Origination Year FE			Yes
Employment Status FE			Yes
Observations	895,802	895,802	895,802
Clusters	391	391	391
Kleibergen-Paap Wald F			6.49
Anderson-Rubin Wald F			8.52 ($p < 0.001$)

Notes: Panel A reports first-stage regressions of risk-segment specific online bank usage on district-level bank branch density per 1,000 inhabitants in 2017 and controls. Branch density captures historical variation in the cost of accessing traditional banking. Panel B reports second-stage two-stage least squares (2SLS) estimates of interest rates on predicted online bank usage within each risk segment. The endogenous variables are $Online_{LowRisk}$ and $Online_{MidRisk}$. The instrument is district-level bank branch density in 2017 interacted with risk bin indicators; both interaction terms enter each first-stage regression. Panel A reports the own-segment instrument coefficient. Risk bins are terciles of predicted default probability derived from a probit model of loan default estimated on borrower characteristics excluding lender type in Equation 2. Pre-sample district-level controls are GDP (ln), population density (ln) (per sq km), and employment rate as of 2017. Standard errors clustered at the NUTS3 district level are reported in parentheses. SW F-stat refers to the Sanderson-Windmeijer first-stage F-statistic for each endogenous variable separately. The Kleibergen-Paap Wald F-statistic tests for weak identification under clustering. The Anderson-Rubin F-stat provides weak-instrument-robust inference on the joint significance of the endogenous regressors.

Table 6: **Falsification Test: Branch Density on Traditional Bank Interest Rate**

	(1) Interest Rate	(2) Default Rate
*BranchDensity*2017	0.127	−0.001
	(0.124)	(0.004)
Region (State) Dummy	Yes	Yes
Loan Origination Year Dummy	Yes	Yes
Employment Status Dummy	Yes	Yes
Borrower & Loan controls	Yes	Yes
Distric (NUTS3) controls (2017)	Yes	Yes
Observations	809,973	809,973
Adjusted R2	0.467	0.015

Notes: This table reports falsification tests for the exclusion restriction of our instrumental variables strategy. The sample is restricted to traditional bank loans only. Column (1) tests whether branch density directly affects traditional bank interest rates. If branch density operated through local banking competition rather than through online bank channel switching, we would expect a negative coefficient: fewer branches imply less competition, leading to higher rates. Column (2) tests whether branch density predicts default among traditional bank borrowers. A significant effect would suggest that branch density correlates with unobserved borrower quality, violating the exclusion restriction.

Table 7: **Borrower Risk Overtime by Lender Type**

	Dep. Var = *RiskScore*	
	(1)	(2)
TraditionalBank × *OriginationYear 2019*	0.020***	0.020***
	(0.001)	(0.001)
TraditionalBank × *OriginationYear 2020*	0.034***	0.034***
	(0.001)	(0.001)
TraditionalBank × *OriginationYear 2021*	0.032***	0.032***
	(0.001)	(0.001)
TraditionalBank × *OriginationYear 2022*	0.022***	0.021***
	(0.001)	(0.001)
TraditionalBank × *OriginationYear 2023*	0.014***	0.014***
	(0.000)	(0.000)
TraditionalBank × *OriginationYear 2024*	0.017***	0.017***
	(0.000)	(0.000)
TraditionalBank × *OriginationYear 2025*	0.022***	0.022***
	(0.001)	(0.001)
OriginationYear 2020	0.005***	
	(0.001)	
OriginationYear 2021	0.005***	
	(0.001)	
OriginationYear 2022	0.002***	
	(0.001)	
OriginationYear 2023	0.002**	
	(0.001)	
OriginationYear 2024	0.003***	
	(0.001)	
OriginationYear 2025	0.004***	
	(0.001)	
Region-Year FE		Y
Adjusted R2 (Within R2)	0.774	0.642
Obs	1,349,886	1,349,886

Notes: This table presents regression results of Equation (8) testing whether traditional banks face a riskier borrower pool as online expands and serves low risk borrowers. The sample includes consumer loans from January 2019 to June 2025, with online banks as the omitted category. *RiskScore* is the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics (income, borrower employment status, region, loan amount, duration, loan purpose, origination year), ranging from 0.0% (=0 lowest risk) to 100.0% (=1 highest risk) (mean = 3.9%, SD = 3.1%, min = 0.2%, max = 17.8%). All specifications include controls for income (ln), loan amount (ln), duration (ln), borrower employment status, borrower region and origination year. Column (1) shows OLS estimates with region and year dummies as controlsand column (2) uses a fixed effects estimator with region-year fixed effects. Standard errors are clustered at the region-year level and reported in parentheses.

Table 8: **Interest Rate Differentials Overtime by Lender Type**

	Dep. Var = Interest rate	
	(1)	(2)
TraditionalBank × *OriginationYear 2019*	2.119***	2.096***
	(0.099)	(0.101)
TraditionalBank × *OriginationYear 2020*	2.566***	2.510***
	(0.138)	(0.146)
TraditionalBank × *OriginationYear 2021*	2.300***	2.247***
	(0.140)	(0.148)
TraditionalBank × *OriginationYear 2022*	2.441***	2.404***
	(0.104)	(0.110)
TraditionalBank × *OriginationYear 2023*	3.366***	3.335***
	(0.086)	(0.090)
TraditionalBank × *OriginationYear 2024*	3.844***	3.811***
	(0.099)	(0.103)
TraditionalBank × *OriginationYear 2025*	4.583***	4.556***
	(0.184)	(0.186)
OriginationYear 2020	−0.422***	
	(0.058)	
OriginationYear 2021	−0.786***	
	(0.058)	
OriginationYear 2022	0.023	
	(0.052)	
OriginationYear 2023	2.082***	
	(0.060)	
OriginationYear 2024	2.122***	
	(0.058)	
OriginationYear 2025	1.937***	
	(0.065)	
Controls	Y	Y
Region-Year FE		Y
Adjusted R2 (Within R2)	0.557	0.409
Obs	1,349,886	1,349,886

Notes: This table presents regression results from Equation (9) testing whether traditional banks face a riskier borrower pool as online expands and serves low risk borrowers. The sample includes consumer loans originated from January 2019 to June 2025, with online banks as the omitted category. All specifications include controls for income (ln), loan amount (ln), duration (ln), RiskScore, borrower employment status, borrower region and origination year. Column (1) shows OLS estimates and column (2) uses a fixed effects estimator with region-year fixed effects. Standard errors are clustered at the region-year level and reported in parentheses.

Table 9: **Interest Rate Pass-through by Lender Type**

	Dep. Var = Interest rate	
	(1)	(2)
OnlineBank	−3.167***	−3.167***
	(0.044)	(0.044)
PolicyRate	0.838***	0.838***
	(0.064)	(0.064)
OnlineBank × *PolicyRate*	−0.263***	−0.263***
	(0.020)	(0.020)
Controls	Y	Y
Region-Year FE		Y
Adjusted R2 (Within R2)	0.565	0.420
Obs	1,349,886	1,349,886

Notes: This table presents regression results testing whether traditional and online banks differentially pass through changes in the ECB policy rate to loan interest rates. The sample includes consumer loans originated from January 2019 to June 2025, with online banks as the reference category. Policy Rate is the ECB deposit facility rate at the time of loan origination. The coefficient on Policy Rate captures the passthrough rate for online banks (reference category), while the interaction term (Online Bank × Policy Rate) captures the differential passthrough for traditional banks relative to online banks. All specifications include controls for income (ln), loan amount (ln), duration (ln), income-loan amount interaction, borrower employment status, borrower region, and origination year. Column (1) shows OLS estimates; column (2) includes region-year fixed effects. Standard errors are clustered at the region-year level and reported in parentheses.

Table 10: **Interest Rate Pass-through by Lender Controlling for Borrower Risk**

	Dep. Var = Interest rate	
	(1)	(2)
PolicyRate	0.594***	0.596***
	(0.057)	(0.058)
OnlineBank	−2.459***	−2.454***
	(0.092)	(0.092)
OnlineBank × *PolicyRate*	0.033	0.041
	(0.045)	(0.045)
RiskScore	46.060***	47.996***
	(6.916)	(7.282)
OnlineBank × *RiskScore*	53.983**	59.679***
	(20.900)	(21.724)
PolicyRate × *RiskScore*	11.843***	11.731***
	(1.662)	(1.729)
OnlineBank × *PolicyRate* × *RiskScore*	−37.307***	−39.544***
	(7.617)	(7.732)
Controls	Y	Y
Region-Year FE		Y
Adjusted R2 (Within R2)	0.569	0.426
Obs	1,349,886	1,349,886

Notes: This table presents regression results testing whether traditional and online banks differentially pass through changes in the ECB policy rate to loan interest rates controlling for borrower risk. The sample includes consumer loans originated from January 2019 to June 2025, with online banks as the reference category. Policy Rate is the ECB deposit facility rate at the time of loan origination. The coefficient on Policy Rate captures the passthrough rate for online banks (reference category), while the interaction term (Online Bank × Policy Rate) captures the differential passthrough for traditional banks relative to online banks. All specifications include controls for income (ln), loan amount (ln), duration (ln), income-loan amount interaction, borrower employment status, borrower region, and origination year. Column (1) shows OLS estimates; column (2) includes region-year fixed effects. Standard errors are clustered at the region-year level and reported in parentheses.

Table 11: **Shift-Share Evidence: Branch Consolidation Exposure and Traditional Bank Borrower Risk**

	Dep. Var = RiskScore	
	(1) Traditional Bank Loans	(2) Online Bank Loans (Placebo Test)
BranchExposure	−0.017**	0.002
	(0.007)	(0.009)
District-level controls	Y	Y
District (NUTS-3) FE	Y	Y
Loan Origination Year FE	Y	Y
Obs	809,973	444,272
Clusters	391	391

Notes: This table reports reduced-form shift-share estimates of the effect of branch consolidation exposure on borrower risk. $BranchExposure_{d,t} = \sum_g Share_{g,d,2017} \times (Branches_{g,t} - Branches_{g,2017})/Branches_{g,2017}$, where g indexes banking groups and shares are computed from 2017 district-level branch composition. More negative values indicate greater exposure to branch consolidation. *RiskScore* is the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics excluding lender type (Equation 2), ranging from 0.0% (=0 lowest risk) to 100.0% (=1 highest risk). Column (1) restricts the sample to traditional bank loans. Column (2) estimates the same specification on online bank loans as a placebo test. District-level controls include GDP (ln), population density (ln), and employment rate. Standard errors are clustered at the NUTS-3 district level and reported in parentheses.

Table 12: **Shift-Share Evidence: Branch Consolidation Exposure and Traditional Bank Interest Rates**

	Dep. Var = Interest rate
	(1) Traditional Bank Loans
BranchExposure	−0.580
	(0.460)
Loan-level controls	Y
District-level controls	Y
District (NUTS-3) FE	Y
Loan Origination Year FE	Y
Obs	809,973
Clusters	394

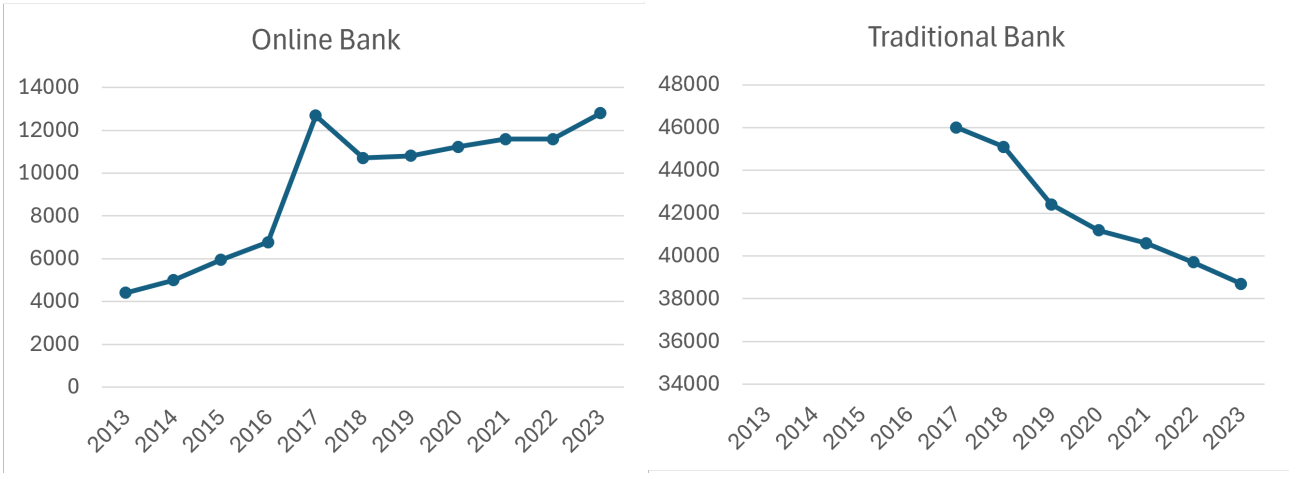
Notes: This table reports reduced-form shift-share estimates of the effect of branch consolidation exposure on traditional bank interest rates. $BranchExposure_{d,t} = \sum_g Share_{g,d,2017} \times (Branches_{g,t} - Branches_{g,2017})/Branches_{g,2017}$, where g indexes banking groups and shares are computed from 2017 district-level branch composition. More negative values indicate greater exposure to branch consolidation. The sample is restricted to traditional bank loans. Loan-level controls include income (ln), loan amount (ln), duration (ln), and borrower employment status. Standard errors are clustered at the NUTS-3 district level and reported in parentheses.

Table 13: **Interest Rate Differentials by Lender Type and Risk: Traditional Bank vs. Fintech**

	Dep. Var = Interest rate	
	(1)	(2)
RiskScore	5.666	3.704
	(8.906)	(9.722)
Fintech	3.388***	3.381***
	(0.251)	(0.250)
Fintech × *RiskScore*	12.394*	13.656**
	(6.325)	(6.779)
Controls	Y	Y
Region-Year FE		Y
Adjusted R2 (Within R2)	0.433	0.279
Obs	1,592,290	1,592,290

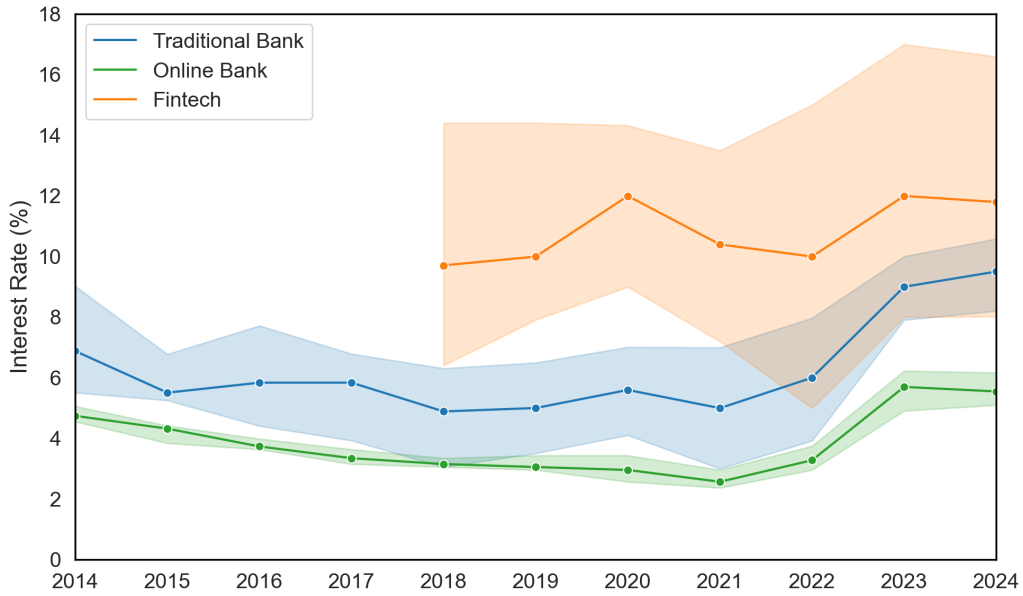
Notes: This table presents regression results examining the interest rate differential between traditional banks and fintech lenders across the borrower risk distribution. The sample includes consumer loans originated from January 2019 to June 2025, with traditional banks as the omitted category. *RiskScore* is the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics, ranging from 0.0% (=0 lowest risk) to 100.0% (=1 highest risk) (mean = 3.9%, SD = 3.1%, min = 0.2%, max = 17.8%). All specifications include controls for loan amount (ln), duration (ln), borrower employment status, borrower region and origination year. Column (1) uses an OLS estimator and column (2) uses a fixed effects estimator with region-year fixed effects. Standard errors are clustered at the region-year level and reported in parentheses.

Figure 1: Consumer credit by bank (USD Bil)



Notes: This figure shows the volume of consumer credit (USD bil.) by a selected sample of banks by bank category. Online bank is ING-DiBa (the largest online bank in Germany by assets). Traditional banks are savings banks and Landesbanks, which together account for 17% of the German consumer credit market in 2024 and represent retail-focused lenders most comparable to online banks.

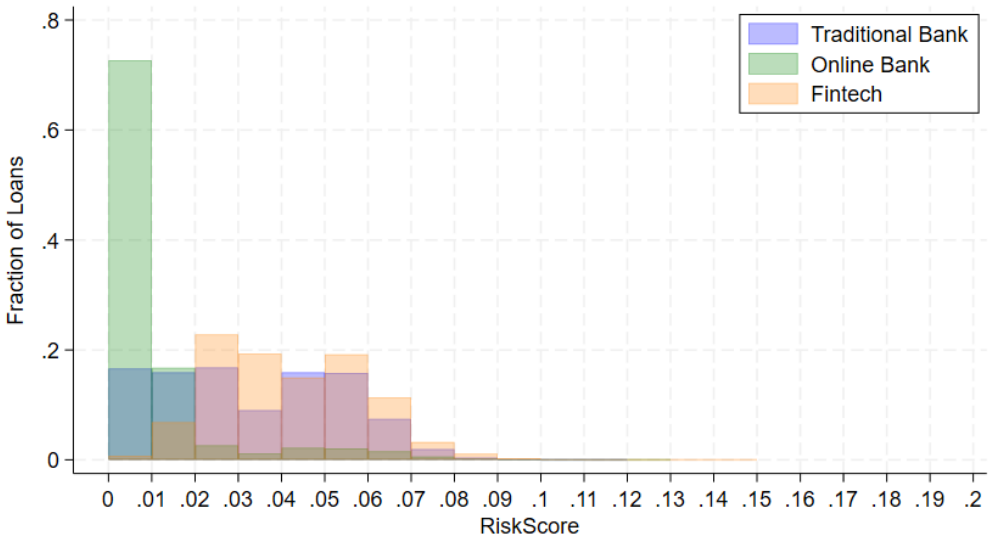
Figure 2: Interest Rates by Lender Type over Time



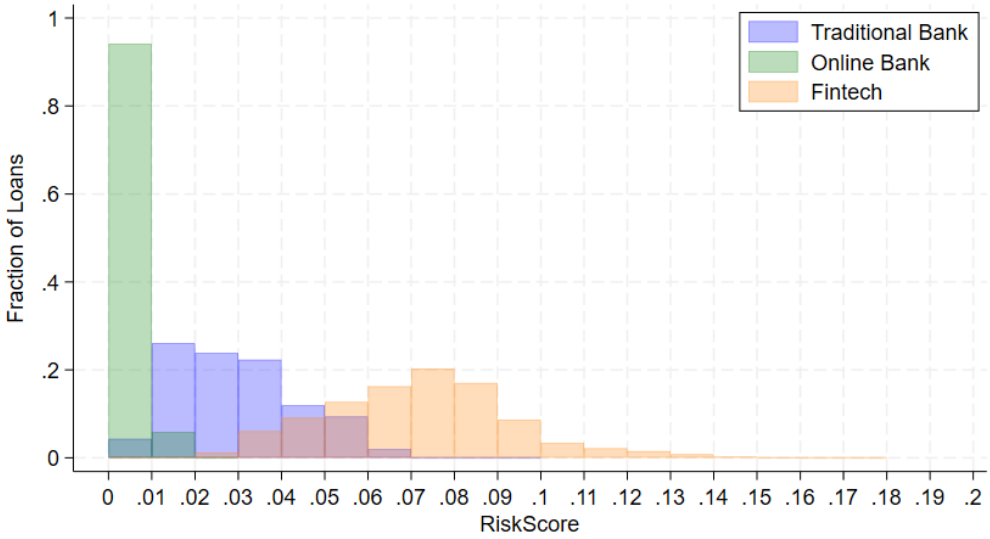
Notes: The figure shows the interquartile range of interest rates for consumer loans originated by different lender types. Data is sourced from the European Data Warehouse (EDW). Loan data for Auxmoney from EDW are only available from 2020 onwards, and the data for 2018 and 2019 are directly obtained from Auxmoney.

Figure 3: Borrower Risk Distribution by Lender Type

Panel A. *Without* lender type in estimation

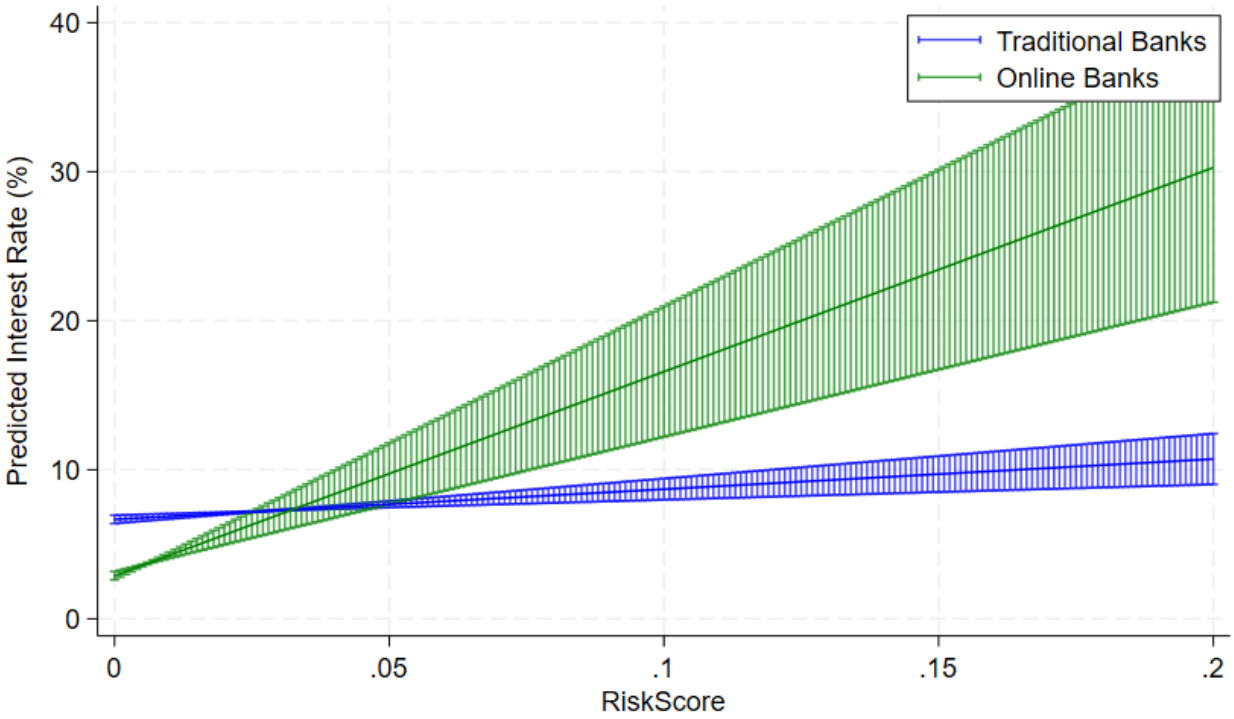


Panel B. *With* lender type in estimation



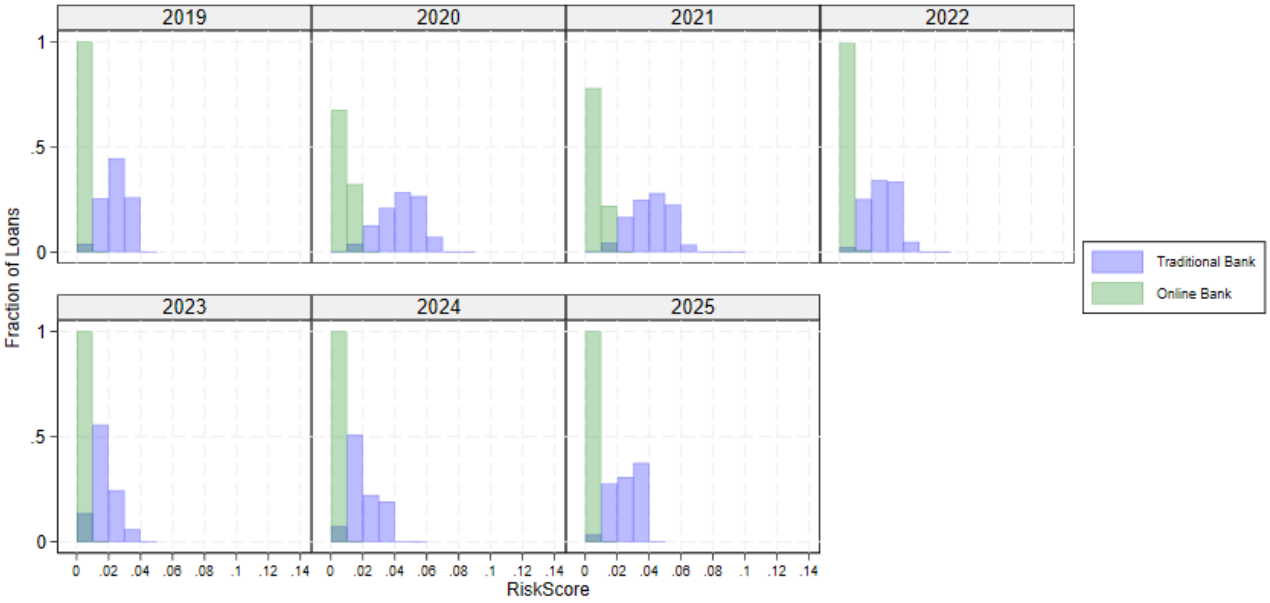
Notes: This figure shows the distribution of *RiskScore* by lender type. *RiskScore* is the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics. Panel A excludes lender type from the estimation; Panel B includes lender type. Mean (SD)—Panel A: Total 3.07% (2.1%), Traditional bank 4.01% (1.94%), Online bank 1.04% (1.29%), Fintech 3.99% (1.78%); Panel B: Total 3.9% (3.1%), Traditional bank 3.50% (1.46%), Online bank 0.48% (0.25%), Fintech 7.16% (2.16%). Covariates include income (ln), loan amount (ln), duration (ln), income (ln) × loan amount (ln), borrower employment status, region, and origination year.

Figure 4: Differential Pricing of Borrower Risk by Lender Type (Model-based Risk Score as Risk Proxy)



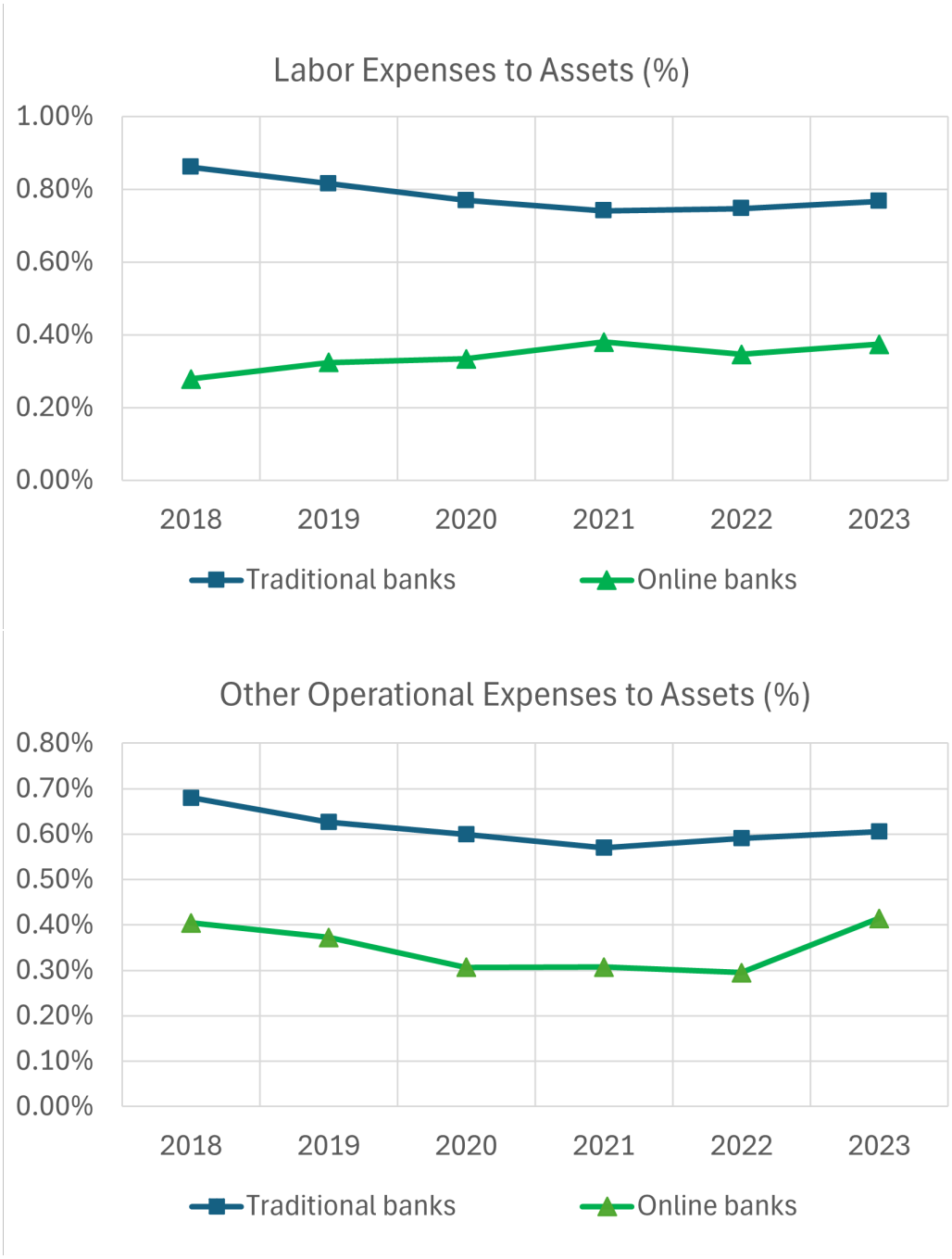
Notes: This figure illustrates how traditional banks and online banks differentially price borrower risk, using *RiskScore* as a risk proxy.*RiskScore* is the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics (income, borrower employment status, region, loan amount, duration, loan purpose, origination year), ranging from 0.0% (=0 lowest risk) to 100.0% (=1 highest risk) (mean = 3.9%, SD = 3.1%, min = 0.2%, max = 17.8%). The figure plots predicted interest rates from a regression that isolates the relationship between rates and risk for each lender type while holding other loan and borrower characteristics constant. Specifically, the figure shows predicted rates from a regression of loan interest rates on *RiskScore* interacted with lender type, controlling for income (ln), loan amount (ln), loan amount (ln) interacted with income (ln), loan duration (ln), lender type, borrower employment status, borrower region, and origination year fixed effects. The blue line shows predicted rates for traditional banks and the green line shows predicted rates for online banks. Shaded areas represent 95% confidence intervals with standard errors clustered at the region-year level. The regression is estimated on January 2019 to June 2025 data. The steeper slope for online banks reveals that their rate advantage over traditional banks diminishes faster as borrower risk increases.

Figure 5: Borrower Risk Distribution Overtime by Lender Type



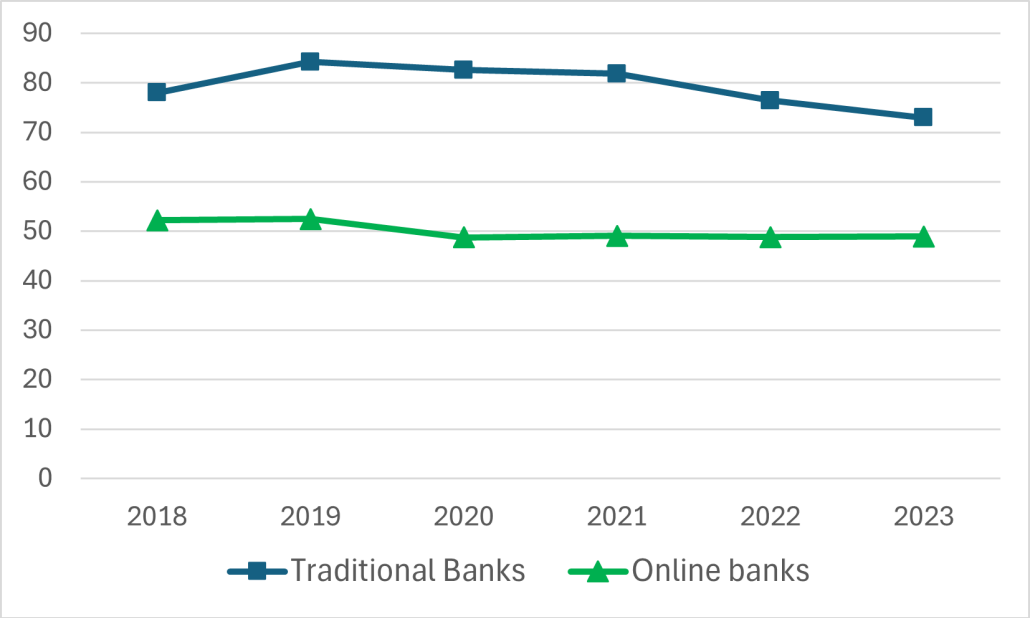
Notes: This figure shows the distribution of *RiskScore* (0-1) overtime by lender type. *RiskScore* is the predicted default probability estimated from a probit model of ex-post loan default on observable borrower and loan characteristics (income (ln), loan amount (ln), duration (ln), income (ln) × loan amount (ln), lender type, borrower employment status, region, origination year), ranging from 0.0% (=0 lowest risk) to 100.0% (=1 highest risk) (mean = 3.9%, SD = 3.1%, min = 0.2%, max = 17.8%).

Figure 6: Cost to assets by bank category



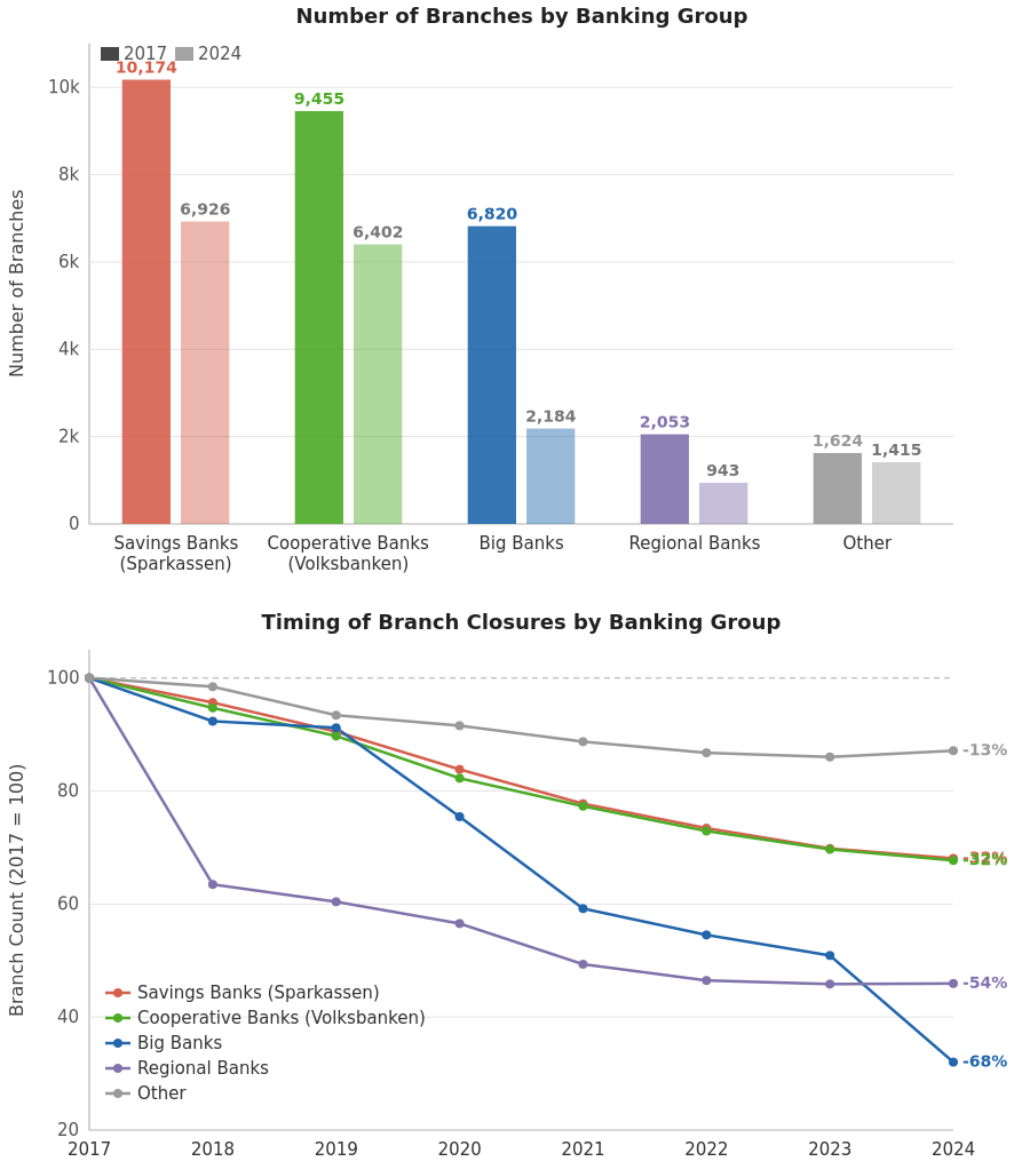
Notes: These figures report non-interest expenses—separately for labor expenses and other operating expenses—scaled by total assets, by bank category in Germany. Big banks include Deutsche Bank, Commerzbank and HypoVereinsbank). The Online banks category includes the three largest direct banks by total assets (ING-DiBa, comdirect, and DKB) and the traditional bank category includes big banks (Deutsche Bank, Commerzbank, and Hypovereinsbank), Savings/Landesbanks, and Credit Cooperatives. Data for Online banks are from FactSet and annual financial reports (value weighted); data for traditional banks are from Factset and annual financial reports (simple averages).

Figure 7: Cost-to-Income (%) by bank category



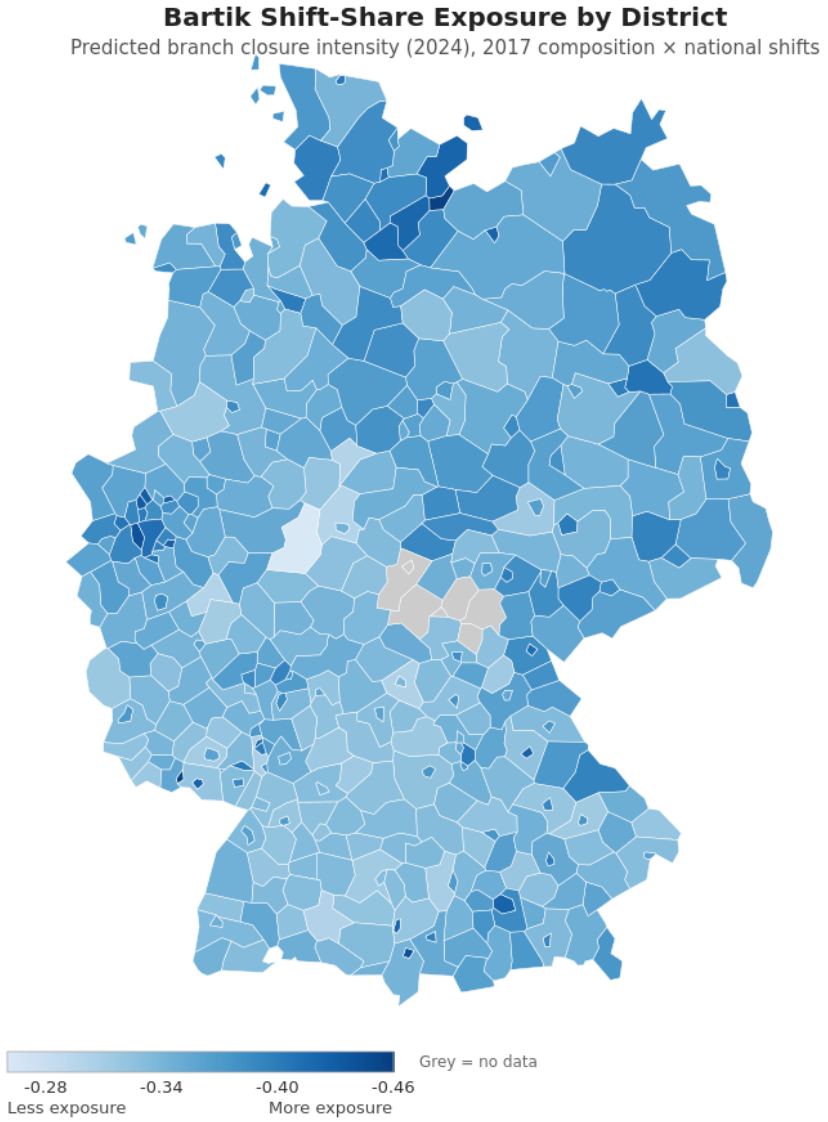
Notes: This figure shows the cost-to-income ratio (CIR) by bank category in Germany. The CIR is defined as general administrative expenses as a percentage of gross earnings (net interest income plus net commission income). Lower values indicate greater operating efficiency. The Online banks category includes the three largest direct banks by total assets (ING-DiBa, comdirect, and DKB) and the traditional bank category includes big banks (Deutsche Bank, Commerzbank, and Hypovereinsbank), Savings/Landesbanks, and Credit Cooperatives. Data for Online banks are from FactSet and annual financial reports (value weighted); data for the remaining bank categories are from the Deutsche Bundesbank, Statistics on Banks and Other Financial Corporations (simple averages).

Figure 8: German bank branch closures (2017-2024)



Notes: This figure displays the number of branches by banking group in 2017 and 2024 (top panel) and the evolution of branch counts indexed to 2017 = 100 (bottom panel). Data are from the Deutsche Bundesbank.

Figure 9: Bartik Shift-Share Branch Exposure by District (2024)



Notes: This figure plots $BranchExposure_{d,t}$ for $t = 2024$ across NUTS-3 districts in Germany. The measure is constructed as $\sum_g Share_{g,d,2017} \times (Branches_{g,2024} - Branches_{g,2017})/Branches_{g,2017}$ where g indexes banking groups and shares are computed from 2017 district-level (NUTS3) branch composition using OpenStreetMap data. The shift-share measures the predicted branch closure intensity. More negative values (darker shading) indicate districts with greater predicted branch losses due to higher initial concentration of aggressively consolidating banking groups. Grey areas indicate districts with no data.

A Additional Tables and Figures

Table A.1: **Loan characteristics by securitization status**

	Weighted Means	
Variable	Unsecuritized loans	Securitized loans
Age	41.252	41.847
Income	2932.817	2084.644
Interest rate	0.104	0.111
Credit score group (max 4, min 1)	3.313	3.261
Loan amount	7535.684	7801.949
Loan duration	55.550	57.662

Notes: This table compares loan characteristics for unsecuritized and securitized loans that were issued after 2019. This is to compare whether the securitized loans are representative of the overall loan portfolios by the lender as mandated by the EU Securitisation Regulation (Regulation (EU) 2017/2402 which became applicable across the EU on 1 January 2019. The data are from the largest German Fintech lending platform, Auxmoney and span from January 2018 to May 2022. Weighted means are computed using the yearly total volume of loans as a share of the total volume as weights.

Table A.2: **Estimation of Predicted Default (Probit)**

	Dep. Var = Ex post default	
Income (ln)	−0.0036***	−0.0016***
	(0.0004)	(0.0002)
Loan amount (ln)	0.0047***	0.0016
	(0.0005)	(0.0010)
Income (ln) × Loan amount (ln)	−0.0004**	−0.0003**
	(0.0001)	(0.0001)
Loan duration (ln)	0.0137***	0.0141***
	(0.0017)	(0.0019)
TraditionalBank		
OnlineBank		−0.0233***
		(0.0012)
Fintech		0.0557***
		(0.0036)
Employed - Public Sector (base)		
Employed − Private Sector	0.0346***	0.0222***
	(0.0007)	(0.0012)
Employed − Sector Unknown	−0.0041***	0.0126***
	(0.0008)	(0.0023)
Other Employment Status	0.0392***	0.0181***
	(0.0021)	(0.0016)
Pensioner	0.0289***	0.0184***
	(0.0013)	(0.0012)
Self−employed	0.0549***	0.0258***
	(0.0028)	(0.0021)
Student	0.0417***	0.0151***
	(0.0023)	(0.0015)
Unemployed	0.0061	0.0358***
	(0.0054)	(0.0129)
Baden-Württemberg (base)		
Bavaria (Bayern)	−0.0045***	−0.0042***
	(0.0008)	(0.0008)
Berlin	−0.0025*	−0.0027**
	(0.0013)	(0.0014)
Brandenburg	−0.0136***	−0.0137***
	(0.0009)	(0.0009)
Bremen	0.0020	0.0023
	(0.0038)	(0.0037)
Hamburg	−0.0033**	−0.0028**
	(0.0016)	(0.0014)
Hesse (Hessen)	−0.0018*	−0.0022**
	(0.0011)	(0.0010)

Table A.2 continued

	Dep. Var = Ex post default	
	Average Marginal Effects	
Mecklenburg−Western Pomerania	−0.0117***	−0.0116***
	(0.0010)	(0.0012)
Lower Saxony (Niedersachsen)	−0.0047***	−0.0047***
	(0.0009)	(0.0009)
North Rhine−Westphalia	−0.0020***	−0.0020***
	(0.0007)	(0.0008)
Rhineland−Palatinate	−0.0037***	−0.0039***
	(0.0010)	(0.0011)
Saarland	0.0061	0.0029
	(0.0049)	(0.0036)
Saxony (Sachsen)	−0.0105***	−0.0110***
	(0.0008)	(0.0008)
Saxony−Anhalt	−0.0080***	−0.0087***
	(0.0012)	(0.0012)
Schleswig−Holstein	−0.0085***	−0.0078***
	(0.0015)	(0.0015)
Thuringia (Thüringen)	−0.0046***	−0.0054***
	(0.0012)	(0.0011)
$OriginationYear$ = 2019 (base)		
$OriginationYear$=2020	0.0160***	0.0211***
	(0.0007)	(0.0014)
$OriginationYear$=2021	0.0254***	0.0193***
	(0.0007)	(0.0012)
$OriginationYear$=2022	0.0213***	0.0038***
	(0.0007)	(0.0014)
$OriginationYear$=2023	0.0178***	−0.0041**
	(0.0008)	(0.0016)
Obs	1,327,270	1,327,270
Pseudo R^2	0.0454	0.0720

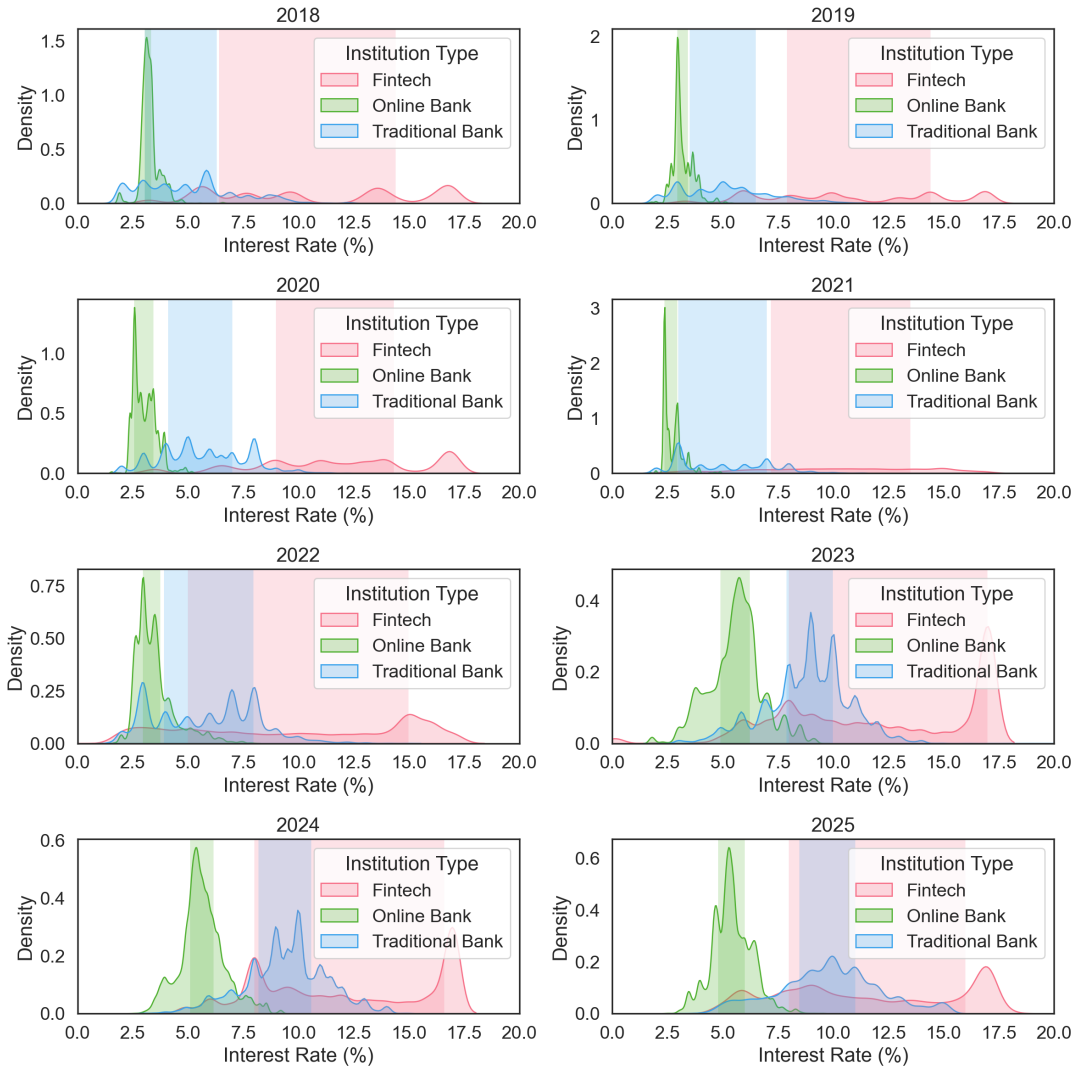
Notes: This table reports average marginal effects from probit regressions estimating the probability of loan default (Equation **??**). Column (1) excludes lender type fixed effects; column (2) includes them. The probit model is estimated using consumer loans originated from January 2019 to December 2023 to allow sufficient time for loans to mature and defaults to be realized. The estimated coefficients are then used to predict default probabilities (*RiskScore*) for all loans in the sample, including those originated in 2024 and 2025. The average predicted default probability for traditional banks (the baseline category in column 2) is 2.97% (SE = 0.06%). Standard errors are clustered at the region-year level and reported in parentheses.

Table A.3: **IV Estimates of Online Bank Interest Rates: Continuous Risk**

	(1)	(2)	(3)
Panel A. First Stage			
	Online	*Online* × *RiskScore*	
BranchDensity2017	−0.055**	0.001	
	(0.023)	(0.000)	
BranchDensity2017 × *RiskScore*	−0.697	−0.084***	
	(0.805)	(0.030)	
Controls	Yes	Yes	
Region (State) FE	Yes	Yes	
Loan Origination Year FE	Yes	Yes	
Employment Status FE	Yes	Yes	
SW F−Stat	14.79	18.37	
Panel B. Second Stage (2SLS)			
			Interest Rate
$\widehat{\textbf{\textit{Online}}}$			−7.839***
			(1.471)
$\textbf{\textit{Online}} \times \widehat{\textbf{\textit{RiskScore}}}$			257.642**
			(115.245)
RiskScore			10.138
			(28.940)
Income (ln)			−0.536***
			(0.200)
Loan Amount (ln)			−0.152***
			(0.047)
Duration (ln)			0.048
			(0.317)
Income (ln) × Loan Amount (ln)			0.046***
			(0.017)
Population density (ln)			0.044***
			(0.017)
GDP (ln)			−0.039***
			(0.015)
Employment rate			−0.014**
			(0.006)
Region (State) FE			Yes
Loan Origination Year FE			Yes
Employment Status FE			Yes
Observations	895,802	895,802	895,802
Clusters	391	391	391
Kleibergen-Paap Wald F			6.94
Anderson-Rubin Wald F			7.55 ($p < 0.001$)
Implied crossover			3.0%

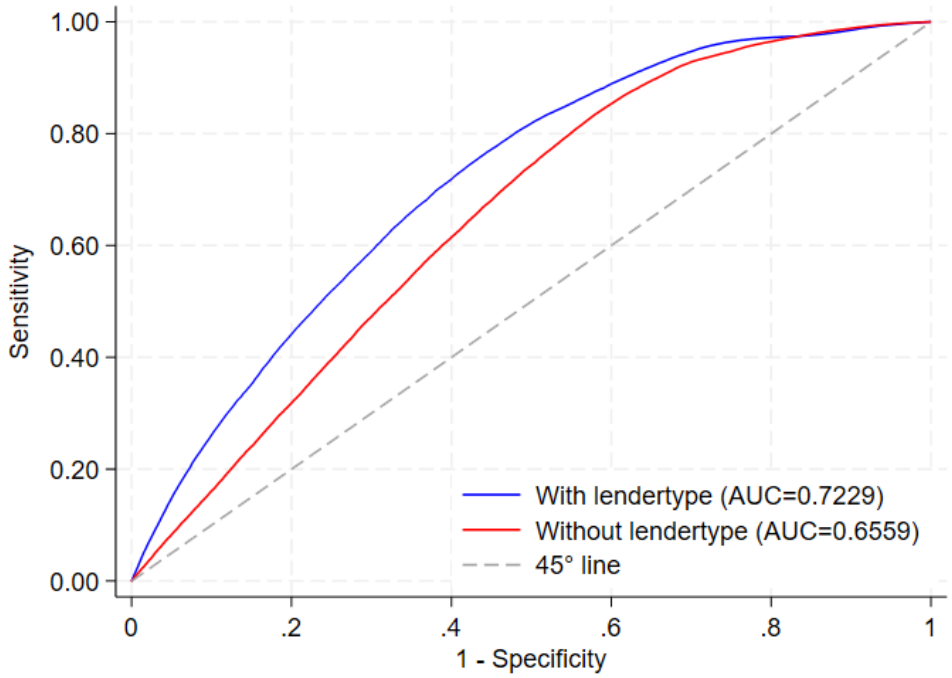
Notes: This table reports IV estimates using continuous credit risk instead of risk bins as in Table 5. Panel A reports first-stage regressions of online bank usage and its interaction with credit risk on district-level bank branch density per 1,000 inhabitants in 2017 and its interaction with credit risk. Panel B reports second-stage 2SLS estimates. The endogenous variables are *Online* and *Online* × *RiskScore*, where *RiskScore* (0-1) is the predicted default probability from a probit model estimated on borrower characteristics excluding lender type in Equation 2. The instruments are *BranchDensity*2017 and *BranchDensity*2017 × *Risk*. The implied crossover point is the risk level at which the online rate advantage equals zero ($-\hat{\beta}_{Online}/\hat{\beta}_{Online \times RiskScore}$). High-risk borrowers (top tercile) are excluded. Pre-sample district-level controls are GDP (ln), population density (ln) (per sq km), and employment rate as of 2017. Standard errors clustered at the NUTS3 district level are reported in parentheses. SW F-stat refers to the Sanderson-Windmeijer first-stage F-statistic for each endogenous variable separately. The Kleibergen-Paap Wald F-statistic tests for weak identification under clustering. The Anderson-Rubin F-stat provides weak-instrument-robust inference on the joint significance of the endogenous regressors.

Figure A.1: Distribution of interest rates by lender type by loan origination year



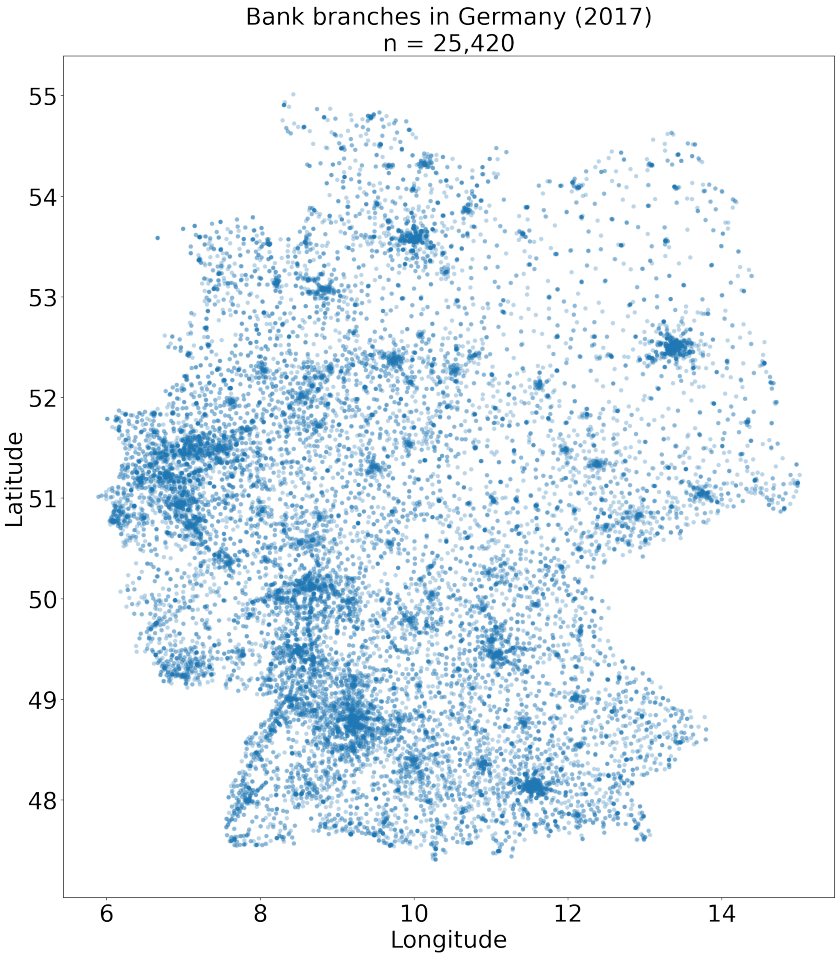
Notes: This plot shows the distribution of interest rates for loans originated by different lender types by year. The shared areas are interquartile ranges. The shaded areas are interquartile ranges.

Figure A.2: ROC Curve for Probit Model of Predicted Default



Notes: This figure displays the receiver operating characteristic (ROC) curves for the probit model of default probability, estimated without (red) and with (blue) the lender type indicator variable (Equation 2 and Equation 3, respectively). The ROC curve plots the true positive rate against the false positive rate at varying classification thresholds, measuring the model's ability to discriminate between defaulting and non-defaulting loans. The area under the ROC curve (AUC) is 0.6559 without lender type and 0.7229 with lender type.

Figure A.3



Notes: This figure plots the geographic distribution of bank branches in Germany in 2017. Each dot represents one physical bank branch location. Branch coordinates are obtained from OpenStreetMap (OSM), an open-source geographic database that provides standardized metadata tags for points of interest. We extract all geo-referenced locations tagged as bank and restrict the sample to establishments within Germany.