Open Banking and Customer Data Sharing: Implications for FinTech Borrowers*

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Abstract

Open banking enables loan applicants to easily and securely share payment data with prospective lenders. In theory, this could broaden credit access by reducing information asymmetry but could also lead to price discrimination that exploits individuals' preferences and behavioral traits. Using loan application data from a leading German FinTech lender in consumer credit, I document that observably riskier applicants (with lower credit scores) are more inclined to disclose data. Data sharing improves loan approvals, reduces interest rates, and is associated with lower ex post defaults. These findings suggest that data sharing via open banking can reduce adverse selection. (*JEL:* D12, G21, G28, G50)

Keywords: Open banking, FinTech, Marketplace lending, Big Data, Customer data sharing

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With the rapid pace of digital transformation, consumer financial activities generate large, high-dimensional, and complex sets of data, known as *Big Data* (Goldstein, Spatt, and Ye 2021). A notable example is payment data, which can offer insights into individuals' cash flow, spending habits, and financial behaviors that are not typically captured in traditional credit reports. In credit markets, prospective borrowers might be inclined to share such data when seeking to switch providers or applying for loans from new lenders. However, consumers often face friction in data sharing as banks may be reluctant to facilitate data transfers due to competitive and security concerns. This can reinforce data monopoly, thereby consolidating the market power of incumbents (Lambrecht and Tucker 2015; de Ridder 2019; Kirpalani and Philippon 2020; Fracassi and Magnuson 2021; Eeckhout and Veldkamp 2022). The lack of adequate infrastructure further complicates data sharing, perpetuating market inefficiencies such as credit rationing and limited choices for borrowers due to high search and switching costs (Jaffee and Russell 1976; Stiglitz and Weiss 1981; Argyle, Nadauld, and Palmer 2023).

Against this backdrop, countries worldwide are adopting open banking, which provides consumers with enhanced control over data sharing. As of October 2021, 80 countries have taken government-led initiatives to promote open banking.[1] In credit markets, this allows borrowers to share their transaction data easily and securely during loan applications.

Exploiting variation in this optional data disclosure and the consequent access to detailed payment data, this paper investigates the following questions: which factors influence data sharing decisions, and does such data sharing benefit borrowers with better financing outcomes? The answers to these questions are not obvious ex ante. Some users will choose to share data due to the perceived benefits (i.e., better financing outcomes), while others may refrain when costs outweigh (i.e., concerns for data misuse and privacy).

Importantly, the impact of data sharing depends on its main use and informativeness beyond existing metrics. If the primary use is to improve credit risk assessments, data sharing can reduce information asymmetry and rationing, thereby enhancing access to credit. On the other hand, it can also open the door to first-degree price discrimination if

[1] See Babina et al. 2024 for an overview of the status of open banking worldwide.

the shared data is used to exploit individuals' preferences and behaviors using advanced algorithms. For instance, lenders may use detailed payment data to infer price sensitivity and search efforts or exploit privacy events to charge higher prices to borrowers who, despite having similar credit risks, are willing to pay more. This practice, made possible by advancements in information technology, aligns with recent theoretical literature that highlights the potential use of data in digital price discrimination. (Bonatti and Cisternas 2020; Ichihashi 2020; Liu, Sockin, and Xiong 2023; He, Huang, and Zhou 2023).[2] Therefore, which of these factors dominates in practice is an empirical question.

To the best of my knowledge, this paper is the first to empirically examine the implications of voluntary data disclosure in open banking contexts within consumer credit markets. I use granular loan application data from Germany's largest FinTech lender in consumer credit and leverage a unique empirical setting where each loan applicant is given the choice to share transaction details during the application process. The dataset consists of more than 2.3 million completed loan applications between 2018 and 2022.

The first question I investigate involves the determinants of data sharing decisions, with a particular focus on observable credit risk as implied by credit scores.[3] The study reveals a higher inclination among observably higher credit risk individuals to consent to data sharing. Specifically, applicants with the lowest credit scores are around 30% more likely to opt in compared to highest score applicants. The likelihood of data sharing monotonically decreases as the credit score increases. The results are robust to controlling for other factors, such as age, that might be driving the data sharing decision and are simultaneously correlated with credit score. At first glance, these findings might appear counterintuitive, given the conventional understanding of adverse selection in financial markets. Traditionally, the prevailing theory suggests that individuals with lower credit risk, who are more likely to have better credit scores, would be more willing to disclose data. Thus, these findings show that the decision to share data is more nuanced.

[2] The EU Consumer Credit Directive/2021 contains an explicit anti-discrimination provision on the basis of nationality, place of residence, sex, race, among other identifiers. First-degree price discrimination, often referred to as personalized pricing, is not directly addressed unless it explicitly discriminates on the protected attributes.

[3] *Schufa* scores, generated by Schufa Holding AG, are Germany's equivalent to the US FICO score. They differ by using a discrete scale from A (best) to M (worst).

To understand this, consider markets with quality uncertainty where private information is held by the borrower. In such environments, good borrowers have incentives to share data to distinguish themselves from others with comparable scores (Viscusi 1978; Grossman 1981; Jovanovic 1982). Data sharing could be a strategy to show their financial behaviors and situations not reflected in credit scores. This could be driven by incentives to obtain better loan terms and/or improve approval odds for those whose latent credit risk is lower than what the score indicates. Importantly, credit scores, while commonly used, may not fully represent a borrower's risk due to limited information, especially for those with lower scores (Albanesi and Vamossy 2019; Gambacorta et al. 2019; Jansen, Nguyen, and Shams 2023). Using ex post defaults, I confirm that this imprecision, measured by mean squared error (MSE), is especially pronounced for those with lower scores. In this context, they have more to gain from disclosing private information because it can address the larger mismatch between the revealed and fundamental credit risk.[4]

Given the decision to share data, the natural next question concerns its impact on financing outcomes. The key is to assess whether this shared data adds substantial information beyond existing metrics. To test this, I quantify the impact of data sharing on loan approvals and interest rates by leveraging variation in data sharing decisions among observably similar applicants using matching. The identifying assumption is that absent data sharing, observably similar applicants should receive similar outcomes. It should be noted that the aim of this exercise is not to assess the impact of data sharing by randomizing these decisions, recognizing their inherently non-random nature. Rather, it intends to examine the consequences of data sharing in light of each individual's strategic decision based on their underlying quality. This aspect sets this paper apart from others that primarily focus on the value of data.

The analyses show that data sharing increases the probability of loan approval by up to 11.7 percentage points and lowers the interest rate by up to 2.2 percentage points. Economically, the effects range from a 1.72% to 43% increase in loan approvals and a

[4]There could be several other factors influencing data sharing decisions, notably concerns for privacy and data misuse (Tang 2019b; Lin 2022). These factors can generally be understood as the cost of data sharing, which would limit information unraveling.

4.1% to 22.3% decrease in interest rates, depending on the credit score group. While data sharing benefits applicants from all credit score groups on average, the impact is particularly pronounced for applicants with lower credit scores on the extensive margin (i.e., a greater increase in the probability of loan approval). This result can be explained by the fact that applicants with high credit scores have ex ante a sufficiently high probability of obtaining a loan, which diminishes the relative impact of data sharing. However, for marginal applicants, even a small improvement in perceived creditworthiness from the shared data can significantly increase their chances of loan approval.[5]

The effects of data sharing on interest rates also show heterogeneity, with high score applicants benefiting from larger reductions in interest rates. This result may appear at odds with the earlier observation that low score applicants face greater credit score imprecision. Given this imprecision, one may anticipate that they would also see more pronounced benefits from data sharing on the loan price. The extent of these benefits, however, may depend on the quality of the data revealed. Following the literature on valuing financial data (Farboodi et al. 2022), I investigate two channels through which data can heterogenously affect loan prices: 1) data reveal information, thus changing the lender's prior about the borrower type, and 2) data reduce uncertainty. To test this, I examine the differences in platform-provided scores (internal scores that incorporate information from the shared data) from observably similar applicants. Assuming that, absent data sharing, observably similar individuals would receive similar platform scores, any improvement in the scores can be at least partially attributed to improvement in the lender's prior as a result of data sharing. If the degree of improvement varies across credit score groups, this suggests heterogeneity in informational content. Additionally, I measure the reduction in uncertainty by first assessing the default forecasting error using MSE and evaluate the degree to which data sharing diminishes risk by measuring the reduction in the standard deviation. I document that the lender's prior improves more, and default predictions become less uncertain after data sharing for high score applicants.

[5]A key question is the equilibrium effect of data sharing, especially if non-disclosers are seen as higher credit risks, reflecting Akerlof's 'market for lemons' concept (Akerlof 1970). As high-quality applicants increasingly share data, those who don't might be perceived as potential 'lemons'. In my empirical investigation, I find a negative yet modest impact on loan approval for non-disclosers.

This implies that data shared by high score applicants contain more positive information and are of higher quality, which could underlie the heterogeneous effects of data sharing on interest rates.

The methodological choice of matching is justified by the fact that the dependent variables – the financing outcomes – are also based on observable applicant characteristics. Hence, this mitigates the concern for confounding factors, as these unobservable aspects are similarly inaccessible to the lender. However, given that I do not have access to the full set of information available to the lender, there still exists the possibility of endogeneity concerns. To address this, I use individual fixed effects by using a subset of applicants with multiple applications, first without and then with data sharing. This approach helps account for unobserved attributes. I find consistent results with the main analyses.

Having established that data sharing benefits loan applicants with higher approval rates and lower interest rates, I turn to ex post defaults to understand the relationship between data sharing and borrower type. By opting to share data, good type borrowers may be strategically revealing unobservable traits, possibly based on their own assessment of their creditworthiness. Thus, data sharing may be a tool for differentiation from an otherwise similar pool of applicants (Viscusi 1978; Grossman 1981; Jovanovic 1982).

I document that data sharing is associated with lower ex post defaults among observably similar borrowers who would otherwise have been pooled in the same risk bracket without the additional data. This finding is in line with the existing theoretical predictions, which claim that under open banking, latent high types are more likely to opt in (He, Huang, and Zhou 2023; Babina et al. 2024). To address potential selection biases arising from using an ex-post loan sample, I conduct a robustness check using the platform score, which is given to all applicants and includes information from the shared data. This yields consistent results. I also account for the direct influence of interest rates on default.

Lastly, I examine the evidence of price discrimination. Price discrimination in this context is conceptualized as akin to first-degree price discrimination, where the lender uses the shared data to infer the highest price that borrowers with similar credit risk are willing to pay. This inference, facilitated by the use of advanced technology, is a concept explored in recent theoretical papers (Bonatti and Cisternas 2020; Ichihashi 2020; Liu, Sockin, and Xiong 2023). Price discrimination is suggested when individuals with similar default probabilities and characteristics get different interest rates. For instance, a person disclosing detailed payment data might be charged more, based on their maximum willingness to pay. By holding the interest rate constant, I show that data sharing has little to no association with ex post defaults, suggestive of limited current evidence of price discrimination. This points to risk pricing as the primary use of shared data.

This study's findings have far-reaching policy implications. The pronounced positive effects of data sharing on loan approvals for those with lower credit scores and without traditional collateral, such as houses, suggest that open banking can be particularly beneficial for asset-light borrowers with thin credit files who are otherwise creditworthy. Importantly, this may give borrowers more choice and flexibility in selecting financial products and could help address hold-up challenges tied to information asymmetry or limited credit avenues (Fracassi and Magnuson 2021). Recognizing the value of consumer financial data, more institutions will pursue access. This trend is occurring alongside an increased focus on consumer privacy and governmental regulations regarding data such as GDRP in Europe. Therefore, customer consent will be an essential element in a data-driven economy, and the implications of this study may extend beyond open banking.[6]

The rest of the paper is organized as follows. Section 1 provides a literature review, and Section 2 describes the data and provides descriptive statistics and preliminary evidence of open banking. Section 3 details the empirical methodology, Section 4 reports the empirical results, and Section 5 presents robustness checks. In Section 6, I provide potential avenues for future research and conclude.

[6]As pointed out by Babina et al. 2024, open banking has some similarities with credit registries (Djankov, McLiesh, and Shleifer 2007; Hertzberg, Liberti, and Paravisini 2011), but it differs in several respects. Open banking data often contain a richer set of information, such as income, spending, and consumption behaviors. While credit registers are centralized databases that only cover consumers with credit products above a certain threshold, open banking data is available for anyone with a bank account. Importantly, these data are updated in real-time, and can be shared with third-party providers for a range of purposes that may extend beyond lending.

1 Related Literature

The existing literature on open banking and sharing consumer payment data is primarily theoretical. Theoretical models indicate that the effects of data portability on welfare may vary with consumers' affiliations with the type of lender (Parlour, Rajan, and Zhu 2022), and whether open banking results in large lender asymmetry favoring FinTech lenders over traditional banks (He, Huang, and Zhou 2023) even when consumers have the option to share data. Providing an empirical perspective, Babina et al. 2024 study the role of open banking in fostering innovation and underscore the dual nature of its effects on consumer welfare, depending on the mode of data utilization. Other studies, such as Goldstein, Huang, and Yang 2022 and Brunnermeier and Payne 2022, provide theoretical perspectives on banking competition, resource allocation, and borrower welfare within the open banking ecosystem.

Building on this largely theoretical foundation, this paper makes several contributions. First, I provide empirical evidence of open banking and customer-driven data sharing by leveraging rich loan application data. The granularity of these data allows for a deeper understanding of the strategic decisions and privacy considerations behind an applicant's choice to share their banking information, extending the literature on optional data disclosure in financial markets. Second, I assess the direct impacts of open banking on loan application outcomes, shedding light on how these data are used in consumer credit contexts. Third, I test the theoretical model predictions from prior studies by investigating the relationship between data sharing practices and borrower types.

Next, I add to the literature examining the role of alternative data in credit markets. Jagtiani and Lemieux 2019 show, by comparing loans from a FinTech lender and banks, that alternative data-based ratings allowed some borrowers to obtain lower-priced credit. Using a German e-commerce platform's data, Berg et al. 2020 show that online user behaviors can predict default risks. Payment footprints can also have higher predictive performance than credit scores (Rishabh 2022). Using BigTech and bank credit, Gambacorta et al. 2020 emphasize that alternative data could minimize the role of collateral, fostering greater financial inclusion. Similarly, Di Maggio, Ratnadiwakara, and

Carmichael 2022 highlight the role of alternative data in spotting invisible primes in the personal loan space; that is, borrowers with low credit scores and short credit histories but also a low propensity to default. This paper provides further evidence of these findings.

My study contributes specifically to the role of payment data in credit risk assessment. Ghosh, Vallée, and Zeng 2021 study the impact of cashless payments by firms on loan application outcomes both at the extensive and intensive margins, using data from a large Indian SME FinTech lender. Exploiting variation in the degree of cashless payments vis-à-vis cash by firms, the authors find that a larger use of cashless payments predicts a higher chance of loan approval, a lower interest rate, and a lower risk-adjusted default rate.[7] This work is the closest to my study in its empirical setting but is different in three ways. First, I use consumer loan data rather than small business loan data. Second, in their loan application, data sharing is mandatory; thus, it does not allow for examining different characteristics among borrowers who do or do not sign up. Last, for the aforementioned reason, their paper does not directly connect to open banking and consumer data rights but rather closely to the value of customer transaction data.

Lastly, I contribute to the growing literature discussing the role of technology in reducing market inefficiencies and disparities. Philippon 2016 highlights that the cost of financial intermediation by traditional players remained surprisingly expensive despite technological advances and has thus resulted in the emergence of new players. Big data are often key to their business models, and they can reduce the impact of negative prejudice in the credit market (Philippon 2019), such as racial disparities, by automating the lending processes (Howell et al. 2021). FinTech lenders also serve in areas with less bank presence, lower incomes, more minority households (de Roure, Pelizzon, and Thakor 2022; Erel and Liebersohn 2022), and higher business bankruptcy filings and unemployment rates (Cornelli et al. 2022).

These new players may directly compete with traditional lenders like banks by serving infra-marginal borrowers who value immediacy and have a higher willingness to pay

[7] In a similar vein, Ouyang 2021 studies the impact of mobile cashless payment on credit provision to the underprivileged, using a sample of Chinese BigTech *Alipay* users and finds a positive impact of in-person payment flow on credit provision.

(Buchak et al. 2018; Tang 2019a) or complement bank lending by absorbing unmet demand (Gopal and Schnabl 2022; Sheng 2021; Avramidis, Mylonopoulos, and Pennacchi 2022; de Roure, Pelizzon, and Thakor 2022). Algorithmic lending can also benefit consumers via more efficient loan application processing (Fuster et al. 2019) and mitigating agency conflicts and humans' limited capacity (Jansen, Nguyen, and Shams 2023). Importantly, FinTech loans can greatly alleviate financing constraints faced by SMEs and further improve access to bank financing by providing uncollateralized loans that can be used to acquire pledgeable assets (Beaumont, Tang, and Vansteenberghe 2022; Eça et al. 2022).

While the above studies underscore the broad operational domains of FinTechs and algorithm lending, my study differs in that it focuses on data sharing within the open banking framework, by analyzing the interaction between individuals' voluntary decisions to share and its impact on borrowers with respect to financing outcomes.

2 Data

2.1 Institutional setting and descriptive statistics

This section provides the institutional background of open banking and the FinTech lender that supplied the data for this study, descriptive statistics, and descriptive evidence of open banking.

2.1.1 Open banking regulation

Open banking repositions data ownership from banks to customers, thus enabling consumers to access and exert more control over how their financial data are shared. As of October 2021, 80 countries worldwide have at least a nascent government-led open banking effort. Most are still in the early-discussion phase, but 32 countries have fully implemented the policy (Babina et al. 2024).[8] The details of open banking regulations

[8] Babina et al. 2024 provide an excellent description of the status of open banking worldwide. In the United States, the Consumer Financial Protection Bureau (CFPB) was tasked under Section 1033 of the Dodd-Frank Act of 2010 to formulate open banking regulations. The CFPB declared in October 2022

differ across jurisdictions. Whereas certain countries impose obligatory data sharing, others merely advise it or offer technical standards and infrastructure to support data sharing.[9] The scope of financial data covered by open banking varies from transaction data to records of savings, lending, and investments. The European Union and the United Kingdom are at the forefront of open banking policies; they are now considering extending the policy. Under the revised Payment Service Directive 2 (PSD2) Access to Account, all European Union institutions offering payment accounts must provide third parties (both banks and non-banks) access to a customer's transactional account information when the customer consents. They are also required to offer dedicated application programming interfaces (APIs)[10] to facilitate secure access. This took effect in January 2016 and was required to be adopted into national laws by January 2018. Given this regulatory environment, Europe serves as a suitable setting to study the impact of customer data sharing on borrowers.[11] For instance, Germany incorporated the directive into its national legal framework on January 13, 2018. As a consequence, this present study considers loan applications from January 13, 2018, to May 22, 2022, ensuring that the legal mandate for open banking-driven data sharing is consistently applied throughout the examined period.

2.1.2 Description of the platform

The original data include approximately 18 million loan applications from the largest German FinTech lending platform, Auxmoney. Founded in 2007, it has originated more than EUR 2.3bn in 319,535 consumer loans between January 2018 and May 2022, and

its aim to establish definitive regulations by 2024, with the execution phase to follow.

[9] Jurisdictions with mandatory data sharing rules include Australia, Bahrain, Brazil, the European Union, and Israel. By contrast, in Singapore, Malaysia, and Russia, banks are recommended to share and regulators facilitate the process by mediating industry discussion, providing technical standards for APIs, or providing infrastructure for data sharing. For more information, see Babina et al. 2024

[10] An API is a software intermediary that allows two applications to communicate with each other. By facilitating customer data sharing among different institutions, APIs play a critical role in securely transferring data and simplifying the customer journey, thus encouraging consumer participation in open banking. Before open banking, sharing bank details was possible, but without an automated process, it was costly and complex for many consumers.

[11] In Europe, open banking is promoted by the European Commission as part of a digital agenda to open up services, provide choice, and foster competition and innovation in the market. For more information, see https://www.openbankingeurope.eu/who-we-are/.

more than EUR 3bn since its inception, making it one of the largest consumer credit marketplace lenders in continental Europe. A prospective borrower can register on the website, enter a desired loan amount anywhere between EUR 1,000 and EUR 50,000, and be guided through an application process during which the applicant is asked to provide a set of personal information and loan details, including loan purpose, employment status, and income and expenses. As a FinTech platform, Auxmoney is not a licensed bank and is thus not subject to banking regulations. To issue loans, it partners with a fully licensed credit institution.

Upon submission of a loan application, the platform evaluates the creditworthiness of the applicant with a platform score: classes AA, A, B, C, D, E, or Z. Those assigned a score of Z are deemed ineligible. In the scoring process, much like traditional banks, the platform initially uses the Schufa (henceforth the “credit score”), a consumer credit rating generated by Schufa Holding AG, a German credit bureau.[12] Unlike traditional banks, which often exclude specific demographics like students, self-employed individuals, or temporary workers deemed to be risky,[13] the platform does not automatically disqualify specific groups. In the preliminary screening, emphasis is placed on an applicant’s historical default records. If applicants meet the criteria in this phase, they advance to a subsequent evaluation, where extensive datasets and digital consumer metrics are employed to compute internal credit ratings, the Auxmoney score (henceforth, the “platform score”). The platform score is primarily derived from five distinct data sources: registration details, credit scores and additional financial information from the credit bureau, behavioral data, web data, and experience data.[14] The entire process is automated, ensuring that in instances of approved applications and agreed-upon loan contracts, loan disbursements typically occur within a few days.

Funding for loans comes from both individual and institutional investors. Initially, the

[12] In contrast to the United States, Germany assigns credit scores without requiring an extensive credit history; even basic financial activities like maintaining a checking account or paying utility bills will yield a credit score

[13] Under stricter banking regulations such as risk-weighted capital requirements, it is costlier to extend credit to high-risk borrowers since a larger capital buffer has to be set aside to service them. This can result in banks reducing lending to high-risk borrowers (Berger and Udell 1994; Kashyap, Stein, et al. 2004; Popov and Udell 2012; Roulet 2018; Benetton et al. 2021).

[14] For more information, https://www.auxmoney.com/faq/auxmoney-score.

platform employed a pure peer-to-peer lending model in which investor and borrower were directly matched. In this disintermediated lending structure, individual lenders selected specific loans to fund, and the platform was not burdened with maturity transformation or information-gathering costs. However, as institutional investors became more involved in the funding process, the platform transitioned to the marketplace model, in which the platform undertakes borrower risk assessment, addressing information asymmetry between retail and institutional lender types and offers diversified loan portfolios (Balyuk and Davydenko 2019; Vallee and Zeng 2019; Braggion et al. 2020). A significant fraction of these loans are now securitized.[15] The study focuses solely on the post-transition period.

2.1.3 Descriptive statistics

As shown in Figure 1, the number of applications on the platform increased steadily over time, except for a noticeable slow down in 2020. Since the beginning of 2021, loan demand on the platform has experienced an uptick, reaching its peak at the end of the sample period. The number of paid-out loans (loan offers accepted by applicants) follows a similar trend.

[Figure 1]

It is important to note that it is also possible for an applicant to submit multiple applications. Successful applicants might do this to compare terms across different loan offers. Meanwhile, rejected applicants might return to the platform and apply again. Including multiple applications from the same applicant in the sample could lead to overweighing this subgroup. Additionally, this study aims to explore both the unconditional probability of data sharing, analyzing how applicants make decisions without prior information, and the subsequent consequences of such decisions. Thus, in the case of multiple applications, only the initial application from each borrower is considered. I also exclude incomplete applications since they lack critical information necessary for the analysis.

[15] Auxmoney has issued three asset-backed security transactions named Fortuna Consumer Loan ABS, comprising approximately 48,000 loans totaling EUR 350 million in 2023, 25,000 loans totaling EUR 225 million in 2022, and 30,000 loans amassing EUR 250 million in 2021.

The final sample consists of 2,309,359 completed loan applications between January 13, 2018, and May 15, 2022.

Table 1 presents the descriptive statistics of the dataset.

[Table 1]

The average requested loan amount on the platform was EUR 13,876, with a typical loan term of 55 months. The mean age of applicants was 38 and 65% were male. The platform approved approximately 68% of these loans, with a mean interest rate of 12%. The average credit score stood at 3.13, based on a 4–1 scale (4 being the best credit score group).[16] The median applicant had a monthly net income of EUR 1,800, and monthly expenses of EUR 600. A majority (94%) had checking account(s), 64% had one or more credit cards. 25% were homeowners, and 57% had at least one automobile. The variables *No. of current loand demand* and *No. past loan demand* provide a proxy for the number of outstanding and previously held loans, respectively. The average applicant is found to have 1.35 active consumer loans and a historical record of around one fully settled loan. The main variable of interest *Signup*, is a dummy variable that takes a value of one if the applicant shared bank transaction data during the loan application process. The average rate of data sharing in the main sample is 8% across the entire sample period. This rate, however, varies significantly across time, reaching over 25% at the end of the sample period in the unrestricted sample. Descriptive statistics broken down by data sharing choices can be found in Table A.1.

Figure 2 provides a timeline of data sharing rate over time. There is a clear upward trend in open banking participation by borrowers over the period under consideration. This consistent increase is observable across all credit score categories, with those in lower credit score groups exhibiting a greater propensity to share information. This observed trend is in line with theoretical expectations that open banking adoption would grow as FinTech lenders refine their business models (He, Huang, and Zhou 2023). The intuition

[16] Numerical values are assigned to the credit score categories such that high scores correspond to higher implied credit quality: 4 for scores A–D (highest), 3 for scores E–G, 2 for scores H–K, and 1 for scores L–M (lowest).

is that over time, FinTech lenders establish their niche markets with improved business models, which enables them to capture more customers.

[Figure 2 and Figure 3]

Younger individuals tend to be more comfortable interacting with technology, which may partially explain the rise in the open banking participation rate. However, as shown in the inter-quartile range of age in Figure 3, applicant age has stayed fairly constant over time.

2.1.4 Data sharing process and descriptive evidence of open banking

The loan application procedure is divided into three phases: (i) application, (ii) decision, and (iii) loan payout and repayment (See Figure A.1). During the application phase, users submit personal details and specify their desired loan amount and duration. They are also given the option to share their transaction details from a bank account.[17] During this process, applicants are presented with an interface detailing the data sharing option and a message describing the potential benefit of providing bank data (i.e., an average discount on a loan), which is shown to everyone. This message may vary over time, albeit at longer intervals. If an applicant opts for data sharing, the platform will gain access to the most recent four months of their banking transactions. Along with presenting the potential benefits of data sharing, the platform also provides applicants with comprehensive and legally mandated information, including a clear outline of how their data will be used. Additionally, the platform discloses that data sharing can have both positive and negative implications. It is stated that while sharing data might offer favorable loan terms for some, it might also lead to negative outcomes for others, such as loan application rejection or a higher proposed interest rate (See Figure A.2).

When the applicant consents to data sharing, this shared information, combined with other sources like credit bureaus, application details, and digital traces, is used to com-

[17]To facilitate this, the platform incorporates a secure API interface provided by a third party, enabling applicants to seamlessly log in to their respective banks. Importantly, the platform employs a three-factor authentication process, ensuring that bank login details remain confidential and are never visible to the platform.

pute the platform score, a proprietary credit scoring system. In the second phase, the decision phase of the process, this platform score, along with the success or failure of the application, is communicated to the applicant, and successful applicants are also provided with an interest rate. In the final, loan payout and repayment phase, the applicant decides to accept or decline the loan offer, leading to either the disbursement of funds or termination of the process. If the applicant accepts the loan, she will proceed to either repay it or default.

Panel A in Figure 4 provides a first glimpse of evidence of open banking. It shows unconditional means of loan acceptance rates by data sharing decisions across different credit score groups. The difference in approval rate between those who do and do not share appears to be larger for applicants from the lower credit score groups. This preliminary evidence aligns with expectations that applicants with good credit scores are typically well positioned for loan approvals, rendering additional data less impactful on the decision of whether to grant a loan.

[Figure 4]

Data sharing is also associated with lower interest rates across applicants of all credit scores (Panel B in Figure 4). Notably, the largest difference in interest rates is seen among highest score applicants. In comparison, there seems to be a more modest difference for applicants from lower credit score groups.

3 Methodology

This section provides the regression models used for the analysis, matching methods and results, and selection bias corrections.

3.1 Probit Analysis of Data Sharing Choices

To estimate the determinants of open banking participation, I use a probit model and estimate the following:

$$\Pr\ (Sign\ up_i = 1) \ = \ \Phi\ (X_i'\beta \ + \ G_i'\gamma \ + \ Year \ + \ \epsilon_i), \tag{1}$$

where i indexes an individual and $Sign\ up_i$ is an indicator variable equal to one if the applicant shares data and zero otherwise. X_i are applicant characteristics, including age, credit score, income, dummy variables indicating gender, main earner, homeowner, car owner, the number of outstanding loans, and fully paid loans. G_i are loan characteristics such as loan amount, loan duration, and loan application channel.[18] $Year$ are year dummies, ϵ_i is the error term, and Φ is the standard normal cumulative distribution function. I am mainly interested in the coefficient β, which measures the change in the likelihood of sharing data across different applicant traits. In particular, the main question is how one's observed credit risk as implied by credit scores, is associated with data sharing. In other words, is it *observably* riskier or safer applicants who are more likely to share data? To this end, the coefficients for each credit score group are of central interest. Later, I also explore how borrower type as implied by ex post defaults, is associated with data disclosure. Standard errors are clustered at the region-year level.

3.2 Matching on observables

The next step examines the effect of open banking participation on loan approval and interest rate. It is important to note that applicants who share data may be *systematically* different from those who do not. Therefore, using the full sample to estimate the effect of *Sign up* on the probability of loan approval or the interest rate may introduce bias. To address this issue, I employ a hybrid matching method to address potential selection bias and ensure comparability between the sharing and non-sharing groups. This approach

[18] Loan access channel is a categorical variable that indicates the channel through which the user applies for a loan. There are five such channels: 1) directly via the Auxmoney homepage, 2) repeat loan, 3) price comparison websites, 4) brokers, and 5) banks.

combines two matching techniques to achieve optimal balance on observed covariates: exact matching and propensity score matching (PSM). Given that borrower traits may differ substantially across access channels[19] and that the data sharing trend fluctuates over time, exact matching is applied to the variables *Access channel* and *Loan application year*, ensuring that these categorical covariates are precisely matched between the treated and untreated groups. On the other hand, PSM is used for *Age*, *Income decile*, and *Credit score*. Using PSM allows for a degree of flexibility, creating matches based on the similarity of propensity scores, which are computed through logistic regression using the three aforementioned variables as predictors.

3.3 Probit Analysis on Data Sharing and Loan Approval

I use the matched sample to estimate the effect of data sharing on the probability of loan approval using a probit model,

$$\begin{aligned}\Pr(Approved_i = 1) = \Phi(&\rho Signup_i + \sigma_k(Signup_i \times Credit\ score\ group_i) \\ &+X_i'\beta + G_i'\gamma + Year + \epsilon_i),\end{aligned} \tag{2}$$

where $Approved_i$ is an indicator variable that takes a value of one if the loan application is approved and zero otherwise. $Sign\ up_i$ is an indicator variable that takes a value of one if the applicant shares data, and zero otherwise. To examine whether data provision has different effects across credit risk groups, I include the interaction term $Sign\ up_i \times Credit\ score\ group_i$. The other variables are the same as in equation (1). The main coefficients of interest are ρ and σ_k which measure the change in the likelihood of loan approval by data sharing decision $Sign\,up_i$, and the differential effect across different credit score groups $k = 4, 3, 2, 1$ (4 (A–D) the best and 1 (L–M) the worst), respectively.[20] It should be noted that matching methods do not account for any unobserved characteristics that may simultaneously determine the data sharing decision and the outcome variable. The omission of such variables may result in endogeneity bias.

[19] See details in Table A.2.

[20] Numerical values are assigned to the credit bureau score (*Schufa*) categories such that high scores correspond to higher implied credit quality: 4 for scores A–D (highest), 3 for scores E–G, 2 for scores H–K, and 1 for scores L–M (lowest).

To address this issue, I focus on a particular group of applicants who submitted multiple applications, initially one without data sharing followed by one or more with data sharing. This method accounts for unobserved individual attributes through fixed effects and distinguishes the data sharing effect. These robustness checks are shown in Section 5. I further apply a Rosenbaum sensitivity analysis to assess the potential influence of unmeasured confounders.

3.4 Data Sharing and Interest Rates

Next, I examine the effect of data sharing on loan interest rates. It is important to note that interest rates are only available for approved loans, leaving a gap in understanding how the decision to share data would have influenced the interest rates of rejected applications. Since the set of approved loans is not a randomly drawn sample, drawing conclusions about interest rates based only on this subset might introduce bias. To rectify this issue, I employ the Heckman correction method to counteract the potential omitted variable bias from this specific sample selection challenge (Heckman 1976; 1979).[21]

I estimate the following equation to assess the effect of data sharing on the interest rate,

$$\begin{aligned} r_i = \theta\hat{\lambda}_i + \rho Signup_i + \sigma_k(Signup_i \times Credit\ score\ group) + X_i'\beta + G_i'\gamma \\ + Year + \epsilon_i, \end{aligned} \tag{3}$$

where r_i indexes interest rate, and $\hat{\lambda}_i$ is the inverse Mills ratio. The other variables are the same as in equation (2). The main coefficients of interest are ρ and σ_k, which respectively measure the change in the interest rate by data sharing decision $Sign\ up_i$ and the differential effect across different credit score categories $k = 4, 3, 2, 1$. A negative θ implies a negative correlation between the error terms and proves the presence of downward selection bias. In other words, applicants with a below-average interest rate and are thus safer are selected for the approved pool of applicants. A priori, the sign of θ is unclear. The platform may prefer borrowers with high interest rates so as to maximize

[21] A model explanation appears in C.

its returns or contrarily select relatively safe borrowers. All the other variables are the same as in equation (1).

4 Main Results

In this section, I present the factors influencing data sharing decisions and their impacts on loan approval rates and interest rates. Then, I introduce economic mechanisms illustrating how data provision influences loan application outcomes. After that, using ex post defaults, I discuss the relationship between data disclosure and latent borrower type and the evidence of price discrimination.

4.1 Factors influencing data sharing decisions

Table 2 reports the estimation results of equation (1) regarding the factors influencing data sharing decisions. Column (1) only includes credit score variables, column (2) only age, column (3) uses both, and column (4) reports all estimates, including all applicant and loan characteristics, access channel, and year dummies. Column (1)–(3) report marginal effects using probit, and Column (5)–(8) report ordinary least squares estimates.

[Table 2]

The results highlight that applicants with *observably* higher credit risk, as measured by lower credit scores, are more likely to share their bank account data than those with better credit profiles. In economic terms, an applicant in the lowest credit score category is on average 3.9 percentage points more likely to share data than an applicant in the highest score category, as illustrated in column (1). The likelihood of data sharing monotonically decreases as credit score improves. This suggests that those with higher scores might be more hesitant to disclose account information. There may be an age-related explanation for this trend. Younger individuals often display a greater willingness to embrace technology and may have shorter credit histories, which results in lower credit scores. To take into account potential confounding factors that could influence the outcome and might be correlated with credit scores, additional controls are included in column (4). Although the magnitudes of the primary coefficients decrease slightly, they remain statistically significant, with a 2.1 percentage point difference between the lowest (L–M) and highest (A–D) credit score categories. Economically, this is a 30% higher likelihood of data sharing given that the average rate of data sharing for the highest (A–D) credit score group is 6.6%.[22] Initially, these results might seem at odds with the standard theory regarding adverse selection, which holds that those with a better credit standing who often having higher credit scores on average, would be typically more inclined to share this information to stand out from the rest. Yet, these findings indicate that data sharing decisions are much more nuanced.

An important factor to bear in mind is the varying incentives across applicants for sharing their data. Theories posit that in markets with quality uncertainty, individuals with higher quality might strategically disclose information to distinguish from the average within the pool (Viscusi 1978; Grossman 1981; Jovanovic 1982). In this framework, for those with high credit scores, the main driving force behind sharing additional information might predominantly be the desire to secure lower interest rates, given that their likelihood of obtaining a loan is already high. In contrast, individuals with lower credit scores might be motivated by a dual purpose: not only to increase their chances of loan approval but also to negotiate lower rates. This dual motivation provides them with a stronger incentive to share more information.

Importantly, credit scores, while commonly used, may not always accurately capture the actual credit risk of a given applicant. Particularly, applicants with lower credit scores might not only have lower credit quality on average, but also be subject to a greater degree of imprecision due to wider variations in the underlying credit factors (Albanesi and Vamossy 2019; Gambacorta et al. 2019; Jansen, Nguyen, and Shams 2023). I use the MSE to test the inference quality of credit scores in predicting defaults. By leveraging ex post default data, I quantify the forecasting error to measure the discrepancy between actual defaults and predictions based on credit scores. A lower mean implies a smaller

[22] Even though this rate of data sharing may appear low, the rate increases substantially over time. The overall rate of data sharing goes from 4% in 2018, to around 15% in 2021 and over 25% in the whole sample. See Figure 2 for details.

error in the prediction model.[23]

[Table 3]

As shown in Table 3, MSE becomes substantially larger for lower credit scores. In other words, credit scores become less precise in predicting default for lower score applicants, and they suffer from more diffuse prior beliefs about underlying credit quality. This suggests that individuals with lower scores might perceive greater potential benefits from indicating high quality using data disclosure, particularly if they believe additional information would better represent their self-assessed creditworthiness.

The results also highlight heterogeneity in data sharing with respect to gender and age. Female applicants are 0.4 percentage point (5%) less likely to sign up than their male counterparts. Holding other factors constant, a 48-year-old applicant is two percentage points (25%) less likely to share data than someone who is 38 years old. These observations align with prior studies that suggest women and older individuals tend to have greater privacy concerns (Goldfarb and Tucker 2012). Individuals who do not own homes are 0.9 percentage point (15.3%) more likely to share data compared to homeowners. Income, on the other hand, does not appear to be an important factor (Tang 2019b). Individuals with more outstanding consumer loans and fully repaid past loans exhibit a higher propensity to share. These results suggest that these applicants may have reached their maximum debt capacity and are thus more financially constrained. Building on the primary analysis conducted with a probit model, I also estimate ordinary least squares regressions as a supplemental analysis (Columns 5–8). The results are consistent, both qualitatively and quantitatively, with those of the main estimates using a probit model.

Beyond this empirical observation, there are other potential explanations not directly explored in this study. Sharing data comes with inherent costs, including concerns for privacy and data misuse (Lin 2022). Additionally, differences in financial literacy regarding how the shared data is used could influence applicant willingness to disclose information.

[23] To mitigate the possibility that the credit score simply captures a mix of other factors that affect defaults, I control for the following borrower and loan characteristics: age, income decile, loan amount, loan duration, female (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable).

4.2 The effect of data sharing on loan approval

In this section, I investigate whether data sharing affects loan approval. Before conducting the probit analysis, I perform the matching procedure described in Section 3.2. The goodness of the matching procedure is assessed with t-tests for the null hypothesis of equal means for both sharing and non-sharing groups. Detailed matching results are reported in Table A.3 and indicate that the matching is successful.[24]

[Table 4]

As Table 4 shows, sharing data improves the probability of loan approval for applicants across all credit score groups, and the magnitudes are both statistically significant and economically sizable. The results reveal a hump-shaped relationship between data sharing and loan approval. Applicants from the second-lowest credit score group (H–K) benefit most with an 11.7 percentage point (45%) increase in the likelihood of loan approval compared to those in the same credit score group who do not share data. This is followed by the lowest credit score group (L–M) who experiences a 3.8 percentage point (28.1%) increase. The effects are relatively less pronounced for the higher score groups (A–D) and (E–G), with a 1.5 p.p (1.72%) and an 8.5 p.p (15.5%) increase, compared to the non-sharing applicants from the respective credit score group.[25]

These findings indicate that mid-low tier applicants are more likely to be on the margin of qualifying for a loan. While the effects are quantitatively sizable, the heterogeneity in its impact is not entirely surprising. Applicants with high credit scores already possess a high probability of obtaining a loan, making the impact of any additional shared data less pronounced. Similarly, for applicants with the lowest credit scores, the effect is also relatively smaller, as their ex ante probability of loan approval is already quite low. By contrast, for those on the margin with borderline credit profiles, even a minor positive

[24] I test including further matching variables such as loan amount and loan duration; the results are both quantitatively and qualitatively similar.

[25] It is important to note that estimating the marginal effect of interaction terms in a non-linear model is not straightforward (see Ai and Norton 2003). To compute the effect of data sharing by credit score group, I obtain margins with nested designs. In this case, each credit score group is treated as a nesting variable over which margins of data sharing are estimated.

shift in perceived creditworthiness due to extra information might turn a likely rejection into an approval.

Notably, home ownership positively affects loan approval rates, an indication that the existence of tangible assets can provide an implicit guarantee for fund recovery in default scenarios. However, the coefficient on the interaction term of home ownership and data sharing is significantly negative, suggesting that data sharing brings more value for applicants without tangible assets.

It should be acknowledged that while matching methods are particularly suitable in this context, given that the outcome variable is determined by the lender based on observable traits, these methods may not fully capture any unobserved characteristics that could be correlated with the data sharing decision and the outcome variable. The limitation stems from the incomplete information set available to the researcher compared to that of the lender. Therefore, the potential exclusion of certain variables might introduce an endogeneity problem. A standard way to address this empirically is by using individual fixed effects. In Section 5, I conduct robustness checks using a subsample of individuals who filed multiple applications with varying data sharing decisions. Using individual-day fixed effects, I account for unobserved individual characteristics.

Having established the link between data sharing and higher loan approval probabilities, a pertinent question arises: what are the equilibrium effects for those who choose not to share data? The concern is whether non-disclosure could be construed as a signal of poor borrower quality, potentially penalizing these individuals in the credit market. I empirically assess these dynamics, and show a modest yet negative impact on non-disclosure (See Appendix B for details).

4.3 The effect of data sharing on loan interest rate

In this section, I investigate whether data sharing affects loan interest rates. It is important to note that interest rates are revealed conditional on loan approval. Therefore, using only a subset of approved loans to estimate the effect of data sharing on interest rates could introduce bias. To address this issue, I employ the two-stage Heckman selection model (see Appendix C).

Table 5 reports the results for the main probit analyses in equation (3). Column (1) reports the baseline results, and column (2) presents estimates after correcting for selection bias using the Heckman two-stage selection model.

[Table 5]

Data sharing leads to lower interest rates across all credit score groups, but the effects are heterogeneous. Those with the highest credit scores experience the largest reduction of 2.26 percentage points (22.3%) compared to their non-disclosing counterparts within the same credit score group. The reductions are comparatively smaller for other groups, at 2.10, 1.37, and 0.61 percentage points (15.9%, 9.5%, and 4.1%) for the E–G, H–K, and L–M groups, respectively. The effects are sizable, given that the average interest rates in the main sample are 8.9%, 12.2% 13.8%, and 14.9% for the A–D, E–G, H–K, and L–M groups, respectively. The coefficient of the inverse Mills ratio is negative and statistically significant, which suggests that there is a downward selection bias; that is, the platform has selected loans with interest rates lower than the average interest rate of the population, and the unselected loans would have been charged higher interest rates.

Notably, home ownership is associated with a reduction in interest rates by 2.3 percentage points. Even though these loans do not require collateral, the existence of such tangible assets may still offer lenders an assurance of potential avenues for debt recovery in case of default. However, when interacted with data sharing, home ownership yields a less pronounced reduction of 1.79 percentage points. In other words, the effect of data sharing is less marked for homeowners than for non-homeowners. This observation underscores the economic parallels between data and collateral (Gambacorta et al. 2020), emphasizing the distinct value of data sharing for those without tangible assets.

In addition to exploring the effect of data sharing on loan approval probabilities and interest rates, I have also investigated its impact on the alignment between requested and approved loan amounts. For this, I created a dummy variable, *FullAmountApproval*, which takes a value of one when the loan amount requested by the applicant is exactly equal to the loan amount approved by the lender. Using a matched sample—where groups are comparable in terms of age, requested loan amount, income, credit score, and application channel and year—I find that applicants who share data are more likely to receive approval for the full amount they request compared to those who withhold information. This suggests that data sharing not only enhances the likelihood of loan approval and lowers borrowing costs but also influences the degree to which borrowers' loan requests are met. This finding provides additional insights into the broader impacts of data sharing in the credit approval process.

4.4 Relationship between data sharing and borrower type using ex post defaults

The choice to disclose data can be seen as a form of self-selection, offering insights into an otherwise unobservable borrower type and possibly reflecting their self-assessed creditworthiness. In theory, data disclosure may allow good borrowers to distinguish themselves from a group of similar applicants (Viscusi 1978; Grossman 1981; Jovanovic 1982). In this section, I investigate the association between data sharing decisions and underlying borrower by looking at whether good types are indeed more likely to share data.

To test this, I use ex post loan payments to infer borrower type[26] and define a loan as in default if payment delay exceeds 90 days. Then, I regress *Default* on data sharing dummy, *Signup*, among observably similar borrowers who would otherwise have been pooled in the same risk bracket. I also control for other variables that could directly influence defaults. The results from Table 6 confirm that data sharing is associated with lower ex post default rates.

[Table 6]

Borrowers with the highest credit scores (ranging from A–D) who choose data sharing have a 1.7 percentage points (24%) lower likelihood of default compared to observably

[26]Data on the payment status of the loans come from the European DataWarehouse, a securitisation repository designated by both the European Securities and Markets Authority and the Financial Conduct Authority. It was established in 2012 as the first securitisation repository in Europe to facilitate the collection, validation, and downloading of standardized loan-level data for asset-backed securities and private whole loan portfolios. For more information, see https://eurodw.eu/.

similar borrowers who refrain from disclosing data. For the lower credit score group (E–G), the difference is 2.3 percentage points (20%), for H-K, it is 2.6 percentage points (16%). This indicates that individuals with an inherently lower risk of default are more predisposed to data sharing.[27]

The analysis thus far offers insights into the relationship between data sharing and borrower type. However, a potential selection issue arises from the fact that defaults are observed only for loans that have been both approved and subsequently taken out by the borrower. This limitation raises concerns that the lower default rates observed among data sharing borrowers might not stem from inherently good borrower types selecting into data sharing. Instead, it could be a result of the lending platform's algorithms effectively identifying and approving better borrowers. This issue is compounded by the lack of visibility into ex post defaults for applicants whose loans were not approved or who chose not to proceed with the loan.

To address this potential bias, I conduct a robustness check as outlined in Appendix D.1. This additional analysis uses the change in platform scores, calculated by the fintech lender, as a proxy for unobserved borrower type. The platform score is an internal credit rating assigned at the end of the application process and incorporates payment data if shared by the applicant. Therefore, the platform score would reflect the private information shared via open banking. This score ranges from seven to one, with one indicating a rejected application. I define a dummy variable *Goodtype* which takes a value of one for platform scores between seven and three and 0 for a score of two. The underlying assumption is that observably similar individuals would receive similar platform scores in the absence of data sharing. If the hypothesis holds true that good types are more likely to share data, we should observe a shift in platform scores among data sharing borrowers. The results are consistent with the main analysis, further confirming that data sharing is indeed associated with improvement in the platform score, lending support to the idea that data sharing serves as a tool for differentiation for borrowers of higher quality.

Considering the influence of data sharing on loan pricing, I also add the interest rate

[27] The results for borrowers with the lowest scores remain indeterminate due to the constraints of a limited sample size.

as a control in a separate regression in the analysis of the following section. This accounts for the potential causal impact of loan prices and defaults, which could arise from moral hazard or inability to pay.

4.5 Assessing the evidence of price discrimination using ex post defaults

In this section, I investigate whether the lender utilizes in-depth transaction data in the context of price discrimination. While the disclosure of such data can enhance the accuracy of credit evaluations through advanced algorithms, it simultaneously presents a risk of first-degree price discrimination. Here, lenders could analyze granular transaction details not only to assess credit risk but also to estimate a borrower's highest willingness to pay. This study conceptualizes price discrimination as a situation where, despite similar default probabilities and observable traits, a borrower who discloses data could be subjected to higher interest rates. This occurs as lenders, drawing on the insights from detailed payment information, may infer the maximum rate a borrower is willing to pay. This process of inferring willingness to pay from shared data aligns with existing theories on digital price discrimination, where personal data is used to extract rents from consumers, a phenomenon enabled by the advancement in information technology (Bonatti and Cisternas 2020; Ichihashi 2020; He, Huang, and Zhou 2023; Liu, Sockin, and Xiong 2023; Babina et al. 2024).

To empirically investigate this, the default dummy, *Default* is regressed on the data sharing dummy, *Signup*, while holding the interest rate constant, thereby isolating the causal impact of interest rate on default. Again, the regression uses a matched sample, including control variables. Fixing the interest rate also allows me to test the existence of price discrimination. Under the premise that the primary function of the shared data is to assess credit risk, one would expect the coefficient of *Signup* to be zero. This outcome would indicate that data sharing does not influence the interest rate beyond what is justified by the risk assessment. However, if the shared data is used for systematic overpricing – charging the maximum price a borrower is willing to pay – a negative coefficient is expected. In such a scenario, even when two individuals exhibit the same default probability, the one who has shared data might face a higher interest rate. This outcome would suggest that the lender is using the additional information from data sharing not merely to evaluate risk, but to infer the highest interest rate a borrower is prepared to pay. Such a finding would be indicative of first-degree price discrimination, where the lender leverages detailed payment data to extract rents from borrowers who disclose their data.

[Table 7]

Table 7 indicates that factoring in the interest rate renders little to no association between data sharing and ex post defaults. This observation underscores that the primary application of the shared data is for evaluating credit risk, and the platform correctly calibrates the risk into the interest rates using the shared data. Therefore, I find limited evidence of price discrimination.

It is worth noting that adding the interest rate in the regression with a matched sample changes the interpretation of the coefficient of data sharing, *Signup*. If Borrower A shares data and receives the same interest rate as Borrower B, this implies that, on average, Borrower A would have received a higher interest rate absent data sharing. Put differently, two borrowers would have been pooled separately without data sharing, with A in a pool with riskier borrowers. By sharing data, Borrower A moves to a better pool with Borrower B and now receives the same interest rate and there is no difference in ex post defaults between these two groups. This is consistent with the suggestion based on theoretical models that unobservably good types differentiate themselves by data sharing (Babina et al. 2024; Parlour, Rajan, and Zhu 2022; He, Huang, and Zhou 2023).

4.6 The channels through which data sharing affects loan application outcomes

The findings from the previous sections highlight the heterogeneous effects of data sharing on credit decisions on both the extensive and intensive margins. On the extensive margin (the effect on loan approval), lower credit scores benefit more from data sharing, and this heterogeneity can be intuitively interpreted. Applicants with high credit scores, who inherently have a higher likelihood of loan approval, experience more muted effects from data disclosures. By contrast, for those with marginal credit profiles, the effects are more pronounced, markedly shifting their approval probabilities from potential rejection to acceptance. On the intensive margin (the effect on the interest rate), it is the high-score applicants who experience larger reductions in interest rates, which may appear at first contradictory considering the more prevalent credit score imprecision among low-score applicants, which opens up greater room for interest reduction. Therefore, this outcome necessitates further examination into the underlying dynamics contributing to this heterogeneity of the effect of data sharing on the interest rate.

Thakor and Merton 2018 suggest that FinTech firms might be more susceptible to trust erosion after borrower defaults relative to traditional banks. Meanwhile, Ben-David, Johnson, and Stulz 2021 emphasize the financial constraints that characterize FinTech lenders, which contrasts with the more stable deposit streams of banks. Drawing on this point, I assume the FinTech lender to be risk-averse and that data can help alleviate uncertainties, as highlighted in the data and information literature (Farboodi and Veldkamp 2020). Then, I examine two primary channels through which data can influence loan prices: 1) the adjustment in the lender's prior about the borrower type because data reveal information and 2) the reduction of uncertainties.

To investigate the first mechanism empirically, I estimate the change in the platform score, which is an internal credit score assigned by the FinTech lender once an application is completed. When an applicant decides to share payment data during the loan application, these data, along with other variables, factor into the platform score calculation. Therefore, should this shared information improve the lender's prior of an applicant's underlying risk, that would translate into more favorable loan prices. To test this supposition, I use a matched sample consisting of two groups who are comparable in observable traits but differ in their data sharing choices. In the lender's eyes, these two applicant groups are largely indistinguishable ex ante, implying that their financing outcomes should not, in theory, demonstrate marked differences. Yet, if the data sharing group consistently achieves higher platform scores than their non-disclosing counterparts, this can at least partially attributed to an improvement in the lender's initial assessment as a result of data sharing.

[Table 8]

As depicted in panel A in Table 8, the magnitude of improvement in the platform score is not uniform, with a notably larger increase observed for high score applicants. Additionally, I test the second mechanism, mitigation of uncertainty, by measuring the effects of data sharing on risk reduction. To this end, I first assess the default forecasting error using MSE and evaluate the degree to which data sharing diminishes risk by measuring the reduction in the standard deviation.

Panel B in Table 8 indicates that the default prediction quality improves with data. Particularly for borrowers with high scores, data sharing leads to a greater reduction in the variability in the prediction errors (standard deviation); thus, predictions become more consistent and less uncertain. Overall, data sharing results in a greater improvement in the lender's prior regarding borrower type and a further reduction in default prediction uncertainty for high-score borrowers, thus providing a rationale for the greater impact of data sharing on loan pricing.

5 Robustness checks

5.1 Fixed effects to eliminate unobserved characteristics

Throughout this study, the effects of data sharing are estimated using matched samples. That is, the applicants who share their data are matched to a group of individuals who do not share data but are otherwise similar in observable characteristics to minimize the omitted variable bias. This methodology is suitable for this context as the dependent variables (loan approval and interest rate) are determined by the lender, who bases decisions on observable characteristics. However, one limitation arises from the fact that not all information accessible to the lender is accessible to the researcher. Consequently, there may still exist unobservable variables correlated with both the decision to share data and simultaneously affect the outcome variables, potentially biasing the results. To address this concern, I employ individual-day fixed effects to examine the robustness of the main findings. On the platform, applicants often file multiple applications on the same day to compare different offers. During this process, a user may first apply without data sharing before changing her mind and deciding to share data. Since there is no change in borrower characteristics in the course of one day, the variation in the user's data sharing decisions within a day allows me to employ stringent individual-day fixed effects. By subsuming away unobserved individual characteristics that may jointly determine the data sharing decision and outcome variables, I test the robustness of the effect of data sharing. The sample consists of 34,610 applications from 6,380 users.

[Table 9]

Table 9 shows results from the robustness tests on both the probability of loan approval and the interest rate. The results are both qualitatively and quantitatively consistent with the main results with matched samples. Compared to high score applicants, low score applicants enjoy a higher increase in the probability of loan approval, with middle-tier borrowers benefiting the most. The effects are smaller for the highest- and lowest-score applicants, which is in line with the hump-shaped relationship found in the main results. The magnitude is marginally higher compared to the main results for the highest two credit score groups (A–D and E–G) and is slightly attenuated for the two lowest credit score groups (H–K and L–M). The effects on the interest rate are also robust quantitatively and qualitatively. Data sharing leads to a larger reduction in the interest rate for high score applicants, and the effect decreases for lower score applicants. Compared to the main results, the magnitude of the reduction in the interest rate is slightly lower for the highest three groups (A–D, E–G, H–K) and higher for the lowest rating group (L–M). I implement a further robustness check using the Rosenbaum sensitivity analysis in D.2 to quantify how severe unmeasured confounding variables must be between the sharing and non-sharing groups to nullify the effect of data sharing. I find consistent results.

6 Conclusion

This paper provides empirical evidence of open banking which enables consumers the choice to share payment data with prospective lenders. Leveraging highly granular loan application-level data from the largest German FinTech lender in consumer credit, I show that the rate of data sharing is higher among observably riskier (lower score) applicants. This result can be attributed to the different incentives that drive data sharing among applicants with varying credit scores. Applicants with lower scores are likely motivated by the dual benefits of increasing their loan approval odds and obtaining more favorable interest rates, while those with high scores, with an ex ante high probability of obtaining a loan, may mostly be motivated by getting a lower interest rate. The higher level of imprecision in default prediction associated with lower credit scores suggests that the potential benefits are greater for this group, which substantiates the observed differences in the rate of data sharing.

Data sharing leads to higher approval rates, with the effect varying across credit score groups. Lower score applicants benefit most on the extensive margin, seeing a greater increase in loan approval probability. For high score applicants, who already have a high ex ante likelihood of loan approval, the impact of additional data is less pronounced. However, for low score applicants, even a minor improvement in perceived credit quality can significantly boost their chances of approval, underlining the role of data sharing in enhancing credit access for marginal borrowers. I also show evidence of negative spillovers impacting those who choose not to share their data, due to perceived negative inference about their credit quality. However, the observed effect is, so far, modest.

Data sharing lowers interest rates, yet the effect also varies, with high score applicants seeing larger reductions. I then investigate channels through which data sharing influences loan prices, 1) revealing information and 2) reducing uncertainty. I show that data shared from high score applicants improve lenders' prior and reduce default predictions errors significantly more than low score applicants. This indicates that the quality of shared data differs across credit score groups, explaining the varied effects on interest rates.

Importantly, data sharing is associated with lower ex post defaults. This is suggestive of latent good type borrowers voluntarily disclosing data to distinguish themselves, in line with theoretical predictions (Viscusi 1978; Grossman 1981; Jovanovic 1982). This result holds even after controlling for the potential direct causal impact of interest rates and selection issues arising from the use of ex-post loan data. There is, so far, limited evidence of price discrimination from exploiting individuals' preferences and behaviors, and the main use of shared data seems to be for risk pricing. These findings suggest that data sharing via open banking can reduce adverse selection.

A few issues remain open for future research. Open banking may generate unintended consequences if it limits banks' ability to extract rents from customer data. As open banking is still a relatively new initiative, future research may empirically test these predictions; that is, the second-order effects of open banking via its impact on incumbents' profitability. Therefore, the findings of this paper should be approached with caution in terms of welfare implications, which are not addressed in this study.

Additionally, this study is related to the effects of open banking in the credit market. The implications of open banking, however, may be markedly different across a wider range of financial services, which need to be taken into consideration to assess the aggregate impact.

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Table 1: **Summary Statistics**

Variable	N	Mean	S.D.	Min	p25	p50	p75	Max
LOAN INFORMATION								
Credit requested	2,309,359	13,876.41	13,068.91	1,000.00	4,000.00	10,000.00	20,000.00	50,000.00
Interest rate*	1,559,902	0.12	0.04	0.00	0.08	0.13	0.15	0.20
Platform score (max 7, min 1)	2,309,359	2.89	1.82	1.00	1.00	2.00	4.00	7.00
Credit score group (max 4, min 1)	2,309,359	3.13	0.87	0.00	3.00	3.00	4.00	4.00
Loan duration	2,309,359	55.51	23.94	0.00	36.00	60.00	84.00	84.00
Application accepted (D)	2,309,359	0.68	0.47	0.00	0.00	1.00	1.00	1.00
Bank account detail shared (D)	2,309,359	0.08	0.27	0.00	0.00	0.00	0.00	1.00
BORROWER CHARACTERISTICS								
Age	2,309,359	38.19	12.51	18.00	28.00	36.00	48.00	69.00
Female (D)	2,309,359	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Married (D)	2,309,359	0.39	0.49	0.00	0.00	0.00	1.00	1.00
Main earner (D)	2,309,359	0.62	0.48	0.00	0.00	1.00	1.00	1.00
No. current loan demand	2,309,359	1.35	1.47	0.00	0.00	1.00	2.00	68.00
No. past loan demand	2,309,359	1.04	1.78	0.00	0.00	0.00	1.00	76.00
INCOME AND EXPENSES								
Total income	2,309,359	2,355.13	1,959.79	0.00	1,500.00	1,998.00	2,650.00	30,388.00
Monthly net salary income	2,309,359	2,085.19	1,658.26	0.00	1,300.00	1,800.00	2,400.00	26,000.00
Child support income	2,309,359	120.30	208.11	0.00	0.00	0.00	204.00	1,513.00
Other income	2,309,359	132.90	489.93	0.00	0.00	0.00	0.00	6,666.70
Total expenses	2,309,359	717.38	613.96	0.00	330.00	600.00	954.00	5,147.00
Housing-related expenses	2,309,359	457.05	383.06	0.00	200.00	425.00	650.00	3,000.00
Credit installments expenses	2,309,359	171.77	330.94	0.00	0.00	0.00	240.00	3,086.00
Other expenses	2,309,359	21.14	114.23	0.00	0.00	0.00	0.00	1,500.00
Insurance expenses	2,309,359	49.87	152.19	0.00	0.00	0.00	0.00	1,420.00
Child support expenses	2,309,359	18.25	98.85	0.00	0.00	0.00	0.00	1,200.00
ASSETS								
Credit card holder (D)	2,309,359	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Checking account owner (D)	2,309,359	0.94	0.24	0.00	1.00	1.00	1.00	1.00
Home owner (D)	2,309,359	0.25	0.44	0.00	0.00	0.00	1.00	1.00
Car owner (D)	2,309,359	0.57	0.50	0.00	0.00	1.00	1.00	1.00

Notes: This table presents summary statistics for the sample. The sample period runs from January 13, 2018, to May 22, 2022. (D) = dummy variable. The monetary unit is EUR. The final sample includes only one application per borrower. In the case of multiple applications, the initial application from each applicant is included. *conditional on loan approval.

Table 2: **What characterizes borrowers who share data?**

	Probit (marginal effects)				Linear Probability Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age (10 years)		−0.020***	−0.018***	−0.019***		−0.019***	−0.017***	−0.018***
		(0.0001)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)
Income decile			0.001***	0.000			0.001***	−0.000
			(0.0001)	(0.0001)			(0.0001)	(0.0001)
Credit score (A–D) (base)								
Credit score (E–G)	0.026***		0.013***	0.009***	0.027***		0.014***	0.009***
	(0.0004)		(0.0004)	(0.0004)	(0.0004)		(0.0004)	(0.0004)
Credit score (H–K)	0.039***		0.019***	0.018***	0.038***		0.019***	0.016***
	(0.0006)		(0.0006)	(0.0006)	(0.0006)		(0.0006)	(0.0006)
Credit score (L–M)	0.039***		0.015***	0.021***	0.034***		0.010***	0.013***
	(0.0011)		(0.0010)	(0.0010)	(0.0008)		(0.0009)	(0.0009)
Loan amount requested (ln)				−0.011***				−0.011***
				(0.0002)				(0.0002)
Loan duration (ln)				−0.003***				−0.006***
				(0.0004)				(0.0005)
Female				−0.004***				−0.005***
				(0.0004)				(0.0004)
Married				0.000				−0.001*
				(0.0004)				(0.0003)
Main earner				0.009***				0.010***
				(0.0005)				(0.0005)
No. current loan demand				0.006***				0.008***
				(0.0001)				(0.0002)
No. past loan demand				0.005***				0.006***
				(0.0001)				(0.0001)
Homeowner				−0.009***				−0.008***
				(0.0005)				(0.0004)
Car owner				0.012***				0.009***
				(0.0004)				(0.0004)
Access channel = Homepage (base)								
Access channel = Repeat				0.115***				0.070***
				(0.0031)				(0.0025)
Access channel = Price comparison website				−0.077***				−0.067***
				(0.0012)				(0.0011)
Access channel = Broker				−0.108***				−0.098***
				(0.0014)				(0.0013)
Access channel = Bank				−0.127***				−0.131***
				(0.0015)				(0.0017)
Constant					0.020***	0.114***	0.094***	0.261***
					(0.0004)	(0.0007)	(0.0009)	(0.0023)
Dummy	Year	Year	Year	Year	Year	Year	Year	Year
Cluster (region-year)	X	X	X	X	X	X	X	X
N	2,309,359	2,309,359	2,309,359	2,309,359	2,309,359	2,309,359	2,309,359	2,309,359
R2	0.0640	0.0724	0.0738	0.1055	0.036	0.040	0.041	0.058

Notes: This table reports the results from equation (1), which estimates the probability that a borrower shares bank data using the full sample. The coefficients (1–3) are marginal effects at means. Clustered standard errors are in parentheses. Columns (1)–(3) reports pseudo R2 and (4)-(6) adjusted R2. The dependent variable is *Signup*, a dummy variable that takes a value of one if the applicant shared data and zero otherwise. In the case of multiple applications, the initial application from each applicant is included.

Table 3: **Credit score predictive accuracy**

(1) Credit score group	(2) N	(3) MSE	(4) S.D.	(5) Min	(6) Max
A–D	26,871	0.0376	0.1705	5.7e-07	1
E–G	22,496	0.0608	0.2029	1.4e-06	0.99
H–K	5,562	0.0818	0.2226	8.9e-06	0.97
L–M	422	0.1065	0.2173	2.4e-07	0.98

Notes: This table demonstrates the imprecision of credit scores in predicting defaults. The imprecision of inference is measured using the mean squared error, denoted as $MSE = E[(Z - E(Z|X))^2]$, where Z represents a binary variable that assumes a value of one if the loan is in default status (i.e., delinquency extending beyond 90 days). A probit model has been used to estimate default probability using credit scores. A lower MSE value suggests a smaller error in the predictive model. Results are presented by credit score groups, with groups A–D representing the highest and groups L–M denoting the lowest credit score categories. The sample comprises loans securitized through the Fortuna Consumer Loan ABS in 2021, 2022, and 2023, totaling EUR 850 million. Loan-level data from European asset-backed securities, sourced from the European DataWarehouse (EDW), are linked with Auxmoney loans using key variables, including income, location, loan amount, loan duration, interest rate, loan disbursement date, occupation type, and loan purpose type. This matching process serves to augment the Auxmoney data with loan payment information from EDW. The final sample includes 55,351 loans. To mitigate the possibility that the credit score simply captures a mix of other factors that affect defaults, I control for the following borrower and loan characteristics: age, income decile, loan amount, loan duration, female (dummy), married (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable).

Table 4: **The effect of the data sharing signup decision on loan approval**

	Probit (marginal effects)			Linear Probability Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Signup	0.020***	0.019***	0.015***	0.020***	0.021***	0.031***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Signup × Credit score (A–D)* (Base)						
Signup × Credit score (E–G)	0.094***	0.095***	0.070***	0.095***	0.094***	0.074***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Signup × Credit score (H–K)	0.148***	0.149***	0.102***	0.145***	0.145***	0.113***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)
Signup × Credit score (L–M)	0.071***	0.069***	0.023***	0.066***	0.064***	0.028***
	(0.009)	(0.010)	(0.009)	(0.007)	(0.007)	(0.007)
Credit score (A–D) (Base)						
Credit score (E–G)	−0.235***	−0.189***	−0.157***	−0.295***	−0.235***	−0.216***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)
Credit score (H–K)	−0.544***	−0.480***	−0.460***	−0.607***	−0.527***	−0.476***
	(0.004)	(0.003)	(0.005)	(0.008)	(0.007)	(0.006)
Credit score (L–M)	−0.778***	−0.730***	−0.734***	−0.806***	−0.716***	−0.620***
	(0.003)	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)
Age		0.007***	0.005***		0.006***	0.005***
		(0.000)	(0.000)		(0.000)	(0.000)
Income decile		0.022***	0.014***		0.019***	0.012***
		(0.000)	(0.000)		(0.000)	(0.000)
Homeowner			0.082***			0.081***
			(0.002)			(0.002)
Signup × Homeowner			−0.082***			−0.074***
			(0.002)			(0.003)
Loan amount requested (ln)			0.012***			0.015***
			(0.001)			(0.001)
Loan duration (ln)			−0.111***			−0.100***
			(0.002)			(0.002)
Female			0.033***			0.034***
			(0.002)			(0.001)
Married			0.039***			0.036***
			(0.002)			(0.001)
Main earner			0.029***			0.018***
			(0.002)			(0.001)
Carowner			0.066***			0.068***
			(0.002)			(0.002)
No. current loan demand			0.019***			0.019***
			(0.001)			(0.001)
No. past loan demand			0.006***			0.007***
			(0.000)			(0.000)
Access channel = Homepage (Base)						
Access channel = Repeat			0.000			−0.072***
			(0.000)			(0.004)
Access channel = Price comp. website			−0.270***			−0.292***
			(0.001)			(0.003)
Access channel = Broker			−0.561***			−0.509***
			(0.005)			(0.007)
Access channel = Bank			−0.461***			−0.450***
			(0.012)			(0.007)
Constant				1.071***	0.711***	1.148***
				(0.004)	(0.004)	(0.008)
Dummy	Year	Year	Year	Year	Year	Year
Cluster (region-year)	X	X	X	X	X	X
N	376,852	376,852	376,852	376,852	376,852	376,852
R2	0.2027	0.2433	0.3523	0.2374	0.2754	0.3545

Notes: This table reports the results from equation (2) which estimates the effect of a prospective borrower's decision to share bank account data (*Signup*, a dummy variable that takes a value of one if the applicant shared data and zero otherwise) on the probability of loan approval using the matched sample. In the case of multiple applications, the initial application from each applicant is included. Each of the 188,453 applicants who shared data is matched one-to-one to create a control group of those who did not share data using hybrid matching. Exact matching is used for the access channel and loan application year, and propensity score matching is used for age, credit score, and income decile. The final sample includes 376,852 loan applications from 375,852 unique applicants.
*The coefficients in columns (1)–(3) show marginal effects at means. Clustered standard errors are in parentheses. Columns (1)–(3) report pseudo R2 and columns (4)–(6) report adjusted R2. It is important to note that estimating the marginal effect of interaction terms in a non-linear model is not straightforward (see Ai and Norton 2003). To compute the effect of data sharing by credit score group, I obtain margins with nested designs. In this case, credit score group is treated as a nesting variable over which margins of data sharing are estimated.

Table 5: **The effect of the data sharing signup decision on interest rates**

	Matched sample	
	(1)	(2)
Signup	−0.0216***	−0.0226***
	(0.0005)	(0.0006)
Signup × Credit score (A-D) (Base)		
Signup × Credit score (E-G)	0.0029***	0.0016***
	(0.0004)	(0.0004)
Signup × Credit score (H-K)	0.0112***	0.0089***
	(0.0005)	(0.0005)
Signup × Credit score (L-M)	0.0198***	0.0165***
	(0.0011)	(0.0011)
Credit score (A-D) (Base)		
Credit score (E-G)	0.0208***	0.0247***
	(0.0002)	(0.0006)
Credit score (H-K)	0.0308***	0.0339***
	(0.0003)	(0.0007)
Credit score (L-M)	0.0382***	0.0538***
	(0.0007)	(0.0011)
Signup × Home owner	0.0041***	0.0048***
	(0.0003)	(0.0003)
Homeowner	−0.0195***	−0.0227***
	(0.0002)	(0.0003)
Age (10 years)	−0.0125***	−0.0148***
	(0.0005)	(0.0004)
Age (10 years) × Age (10 years)	0.0006***	0.0008***
	(0.0001)	(0.0001)
Income decile	0.0018***	−0.0018***
	(0.0001)	(0.0001)
Loan amount requested (ln)	0.0099***	0.0089***
	(0.0004)	(0.0004)
Loan duration (ln)	0.0046***	0.0080***
	(0.0003)	(0.0005)
Married	−0.0055***	−0.0067***
	(0.0003)	(0.0003)
Female	−0.0023***	−0.0024***
	(0.0002)	(0.0002)
Main earner	−0.0025***	−0.0017***
	(0.0003)	(0.0003)
Car owner	−0.0044***	−0.0043***
	(0.0002)	(0.0002)
Credit card holder	−0.0065***	−0.0065***
	(0.0002)	(0.0002)
Checking account owner	−0.0016***	−0.0016***
	(0.0004)	(0.0004)
No. current loan demand	−0.0009***	−0.0009***
	(0.0001)	(0.0001)
No. past loan demand	−0.0001**	−0.0001**
	(0.0000)	(0.0000)
Access channel=Homepage		
Access channelr=Repeat	−0.0252***	−0.0259***
	(0.0005)	(0.0009)
Access channel=Price comp. website	0.0064***	0.0060***
	(0.0003)	(0.0003)
Access channel=Broker	0.0193***	0.0188***
	(0.0005)	(0.0006)
Access channel=Bank	0.0214***	0.0203***
	(0.0012)	(0.0013)
Inverse Mills ratio		−0.0129***
		(0.0013)
Constant	0.0761***	0.0793***
	(0.0011)	(0.0012)
Dummy	Year	Year
Cluster (region-year)	X	X
N	249,240	249,240
Adjusted R2	0.4483	0.4491

Notes: This table reports the results of equation (3), which estimates the effect of a prospective borrower's decision to share bank account data (*Signup*, a dummy variable that takes a value of one if the applicant shared data and zero otherwise) on the interest rate conditional on loan approval, using the matched sample. In the case of multiple applications, the initial application from each applicant is included. Column (2) shows the results after correcting for selection bias using the Heckman selection model discussed in Section 3.4 (see C for more detail). Each of the 125,889 approved loan applicants that shared data is matched one-to-one to create a control group of those who did not share data using hybrid matching. Exact matching is used for the access channel and loan application year, and propensity score matching is used for age, credit score, and income decile. The final sample includes 249,240 loan applications from 249,240 unique applicants.

Table 6: **Data sharing decisions and borrower type using ex post defaults**

	Default = 1 if payment is more than 90 days late			
Credit score group	(A–D)	(E–G)	(H–K)	(L–M)
Signup	−0.017***	−0.023***	−0.026***	0.013
	(0.003)	(0.004)	(0.010)	(0.037)
Controls	Y	Y	Y	Y
Cluster (region-year)	Y	Y	Y	Y
N	15,784	15,416	3,761	166
Pseudo R2	0.0421	0.0394	0.0404	0.1263

Notes: This table shows the association between data sharing decisions (*Signup*, a dummy variable that takes a value of one if the applicant shared data and zero otherwise) and *Default* (a dummy variable that takes a value of one if the loan has been late over 90 days). A probit model with a matched sample is used for the analysis. Each column represents a credit score group, with (A–D) being the highest and (L–M) being the lowest. The sample comprises loans securitized through the Fortuna Consumer Loan ABS in 2021, 2022, and 2023, totaling EUR 850 million. Loan-level data from European asset-backed securities, sourced from the European DataWarehouse (EDW), are linked with Auxmoney loans using key variables, including income, location, loan amount, loan duration, interest rate, loan disbursement date, occupation type, and loan purpose type. This matching process serves to augment the Auxmoney data with loan payment information from EDW. The final sample includes 55,612 loans, of which 20,130 borrowers who shared data are matched one-to-one to create a control group of those who did not share data using hybrid matching. The matched sample includes 35,127 loans. Exact matching is used for the access channel and loan application year, and propensity score matching is used for age, credit score, loan amount, loan duration, and income decile. Control variables include age, income decile, loan amount, loan duration, female (dummy), married (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable).

Table 7: **Testing the evidence of price discrimination using ex post defaults**

	Default = 1 if payment is more than 90 days late			
Credit score group	(A–D)	(E–G)	(H–K)	(L–M)
Signup	−0.005	0.000	−0.007	0.022
	(0.003)	(0.005)	(0.011)	(0.068)
Interest rate (%)	0.007***	0.011***	0.012***	0.006
	(0.000)	(0.001)	(0.002)	(0.013)
Controls	Y	Y	Y	Y
Cluster (region-year)	Y	Y	Y	Y
N	15,784	15,416	3,761	166
Pseudo R2	0.0757	0.0647	0.0635	0.0477

Notes: This table shows if there is any evidence of price discrimination using ex post defaults. *Default* (a dummy variable that takes a value of one if the loan has been late over 90 days) is regressed on *Signup* (a dummy variable that takes a value of one if the applicant shared data and zero otherwise) holding interest rate fixed. A probit model with a matched sample is used for the analysis. Each column represents a credit score group, with (A–D) being the highest and (L–M) being the lowest. The sample comprises loans securitized through the Fortuna Consumer Loan ABS in 2021, 2022, and 2023, totaling EUR 850 million. Loan-level data from European asset-backed securities, sourced from the European DataWarehouse (EDW), are linked with Auxmoney loans using key variables, including income, location, loan amount, loan duration, interest rate, loan disbursement date, occupation type, and loan purpose type. This matching process serves to augment the Auxmoney data with loan payment information from EDW. The final sample includes 55,612 loans, of which 20,130 borrowers who shared data are matched one-to-one to create a control group of those who did not share data using hybrid matching. The matched sample includes 35,127 loans. Exact matching is used for the access channel and loan application year, and propensity score matching is used for age, credit score, loan amount, loan duration, and income decile. Control variables include age, income decile, loan amount, loan duration, female (dummy), married (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable).

Table 8: **Channels through which data sharing affects loan application outcomes**

A. Data reveals type (change in platform scores)

	Dependent variable = *Platform score*			
	(A–D)	(E–G)	(H–K)	(L–M)
Signup	0.7732***	0.6619***	0.3798***	0.0999***
	(0.0088)	(0.0072)	(0.0077)	(0.0094)
Dummy	Year	Year	Year	Year
Controls	X	X	X	X
Cluster (region-year)	X	X	X	X
N	122,906	155,868	64,180	14,362
Adjusted R2	0.3449	0.3223	0.3333	0.4658

Notes: This table reports the results of data sharing (*Signup*, a dummy variable that takes a value of one if the applicant shared data and zero otherwise) on the change in the platform score by credit score group, using the matched sample. Control variables include age, income decile, loan amount, loan duration, female (dummy), married (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable). The dependent variable, *Platform score*, ranges from 7 (highest) to 1 (lowest and rejected). Each of the 178,658 loan applicants who shared data is matched one-to-one to create a control group of those who did not share data using hybrid matching. Exact matching is used for the access channel and loan application year, and propensity score matching is used for age, credit score, and income decile. The final sample includes 357,316 loan applications (357,316 unique applicants). Each column represents a credit score group with (A–D) being the highest and (L–M) being the lowest credit score group.

B. Data mitigates uncertainty

	Shared	Not shared	Shared	Not shared	Shared	Not shared
	A–D		E–G		H–M	
N	7,892	7,892	7,708	7,708	1,955	1,955
MSE	0.0485	0.0628	0.0788	0.0967	0.1138	0.1290
Std.	0.1871	0.2052	0.2182	0.2279	0.2309	0.2338
Reduction in Std	8.82%		4.26%		1.24%	

Notes: This table presents the imprecision of platform scores in predicting defaults and the reduction in variance by credit score group. The imprecision of inference is measured using the mean squared error, denoted as $MSE = E[(Z - E(Z|X))^2]$, where Z represents a dummy variable that takes a value of one if the loan is in default status (delinquency extending beyond 90 days) and zero otherwise. A probit model has been used to estimate the default probability using platform scores. A lower MSE value suggests a smaller error in the predictive model. Results are presented by credit score groups, with groups A–D representing the highest and group H–M denoting the lowest group (due to insufficient observations of the previous denoted L-M group, H–K and L–M are combined for this analysis). The sample comprises loans securitized through the Fortuna Consumer Loan ABS in 2021, 2022, and 2023, totaling EUR 850 million. Loan-level data from European asset-backed securities, sourced from the European DataWarehouse (EDW), are linked with Auxmoney loans using key variables, including income, location, loan amount, loan duration, interest rate, loan disbursement date, occupation type, and loan purpose type. This matching process serves to augment the Auxmoney data with loan payment information from EDW. The final sample includes 55,612 loans, of which 20,130 borrowers who shared data are matched one-to-one to create a control group of those who did not share data using hybrid matching. The matched sample includes 35,110 loans. Exact matching is used for the access channel and loan application year, and propensity score matching is used for age, credit score, loan amount, loan duration, and income decile. Control variables include age, income decile, loan amount, loan duration, female (dummy), married (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable).

Table 9: **Robustness checks using fixed effects**

A. The effect of data sharing decision on loan approval

	Credit score			
	(A–D)	(E–G)	(H–K)	(L–M)
Signup	0.035***	0.093***	0.092***	0.042***
	(0.012)	(0.008)	(0.008)	(0.011)
Controls	Y	Y	Y	Y
Individual-day FE	Y	Y	Y	Y
N	4,766	15,922	11,313	2,609
Adjusted R2	0.051	0.072	0.086	0.071

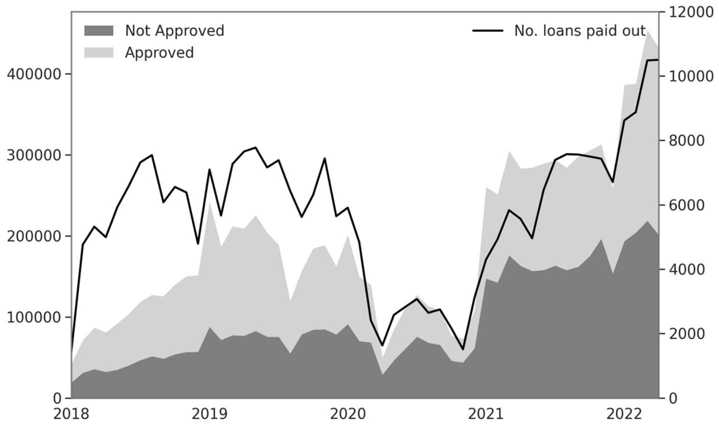
Notes: This table shows the effect of data sharing on the probability of loan approval. The sample includes multiple applications filed by the same individuals on the same day. These individuals do not share their data in initial applications but do share it in others. Given that there is within-individual variation in data sharing decisions while borrower characteristics do not change in the course of one day, I employ individual-day fixed effects to test the effect of data sharing on loan approval as a robustness check. Control variables include loan amount and loan duration. The dependent variable is a dummy variable that takes a value of one if the loan application is approved and 0 otherwise. *Signup* is a dummy variable that takes a value of one if the applicant shared data and zero otherwise. Each column represents a credit score group, with (A–D) the highest and (L–M) the lowest.

B. The effect of data sharing decision on interest rate

	Credit score			
	(A–D)	(E–G)	(H–K)	(L–M)
Signup	−0.017***	−0.014***	−0.007***	−0.007**
	(0.001)	(0.001)	(0.001)	(0.003)
Controls	Y	Y	Y	Y
Individual-day FE	Y	Y	Y	Y
N	3523	5625	1580	135
Adjusted R2	0.217	0.181	0.098	0.068

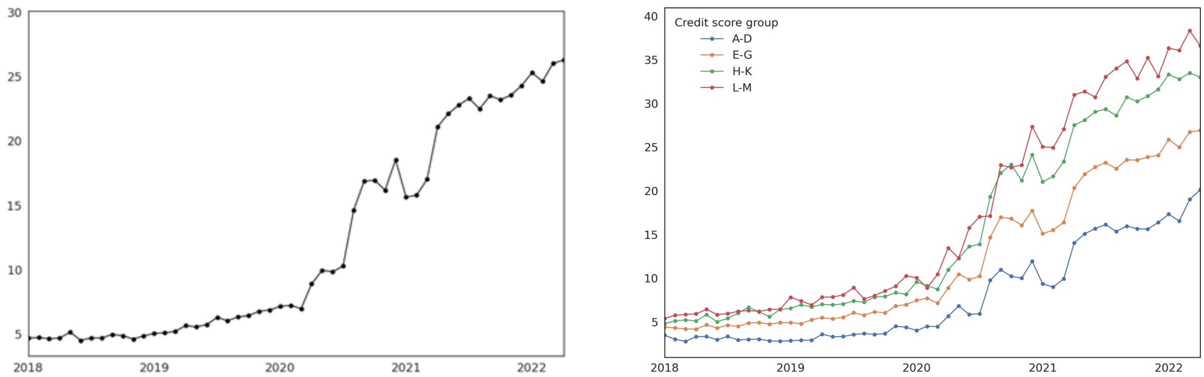
Notes: This table shows the effect of data sharing on the interest rate. The sample includes multiple applications filed by the same individuals on the same day. These individuals do not share their data in initial applications but do share it in others. Given that there is within-individual variation in data sharing decisions while borrower characteristics do not change in the course of one day, I employ individual-day fixed effects to test the effect of data sharing on loan approval as a robustness check. Control variables include loan amount and loan duration. The dependent variable is the loan interest rate conditional on the application being approved. *Signup* is a dummy variable that takes a value of one if the applicant shared data and zero otherwise. Each column represents a credit score group, with (A–D) the highest and (L–M) the lowest.

Figure 1: Number of applications and disbursed loans, measured monthly



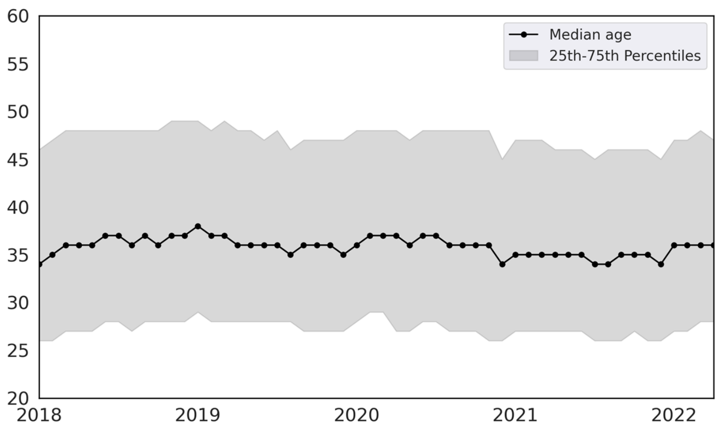
Notes: The figure depicts the monthly count of loan applications, differentiated by approval status. The dark gray bars represent the number of non-approved applications, while the light gray bars indicate approved applications (both plotted on the first y-axis). The second y-axis displays the count of disbursed loans among the approved applications. The sample period is from January 13, 2018 to May 22, 2022.

Figure 2: Data sharing over time (overall vs. by credit score, measured monthly)



Note: The left side of panel shows the percentage of loan applications in which applicants shared their data, calculated as a fraction of the total number of loan applications (including multiple applications per borrower). The right panel illustrates these percentages by applicants' credit score group (A–D: highest, L–M: lowest).

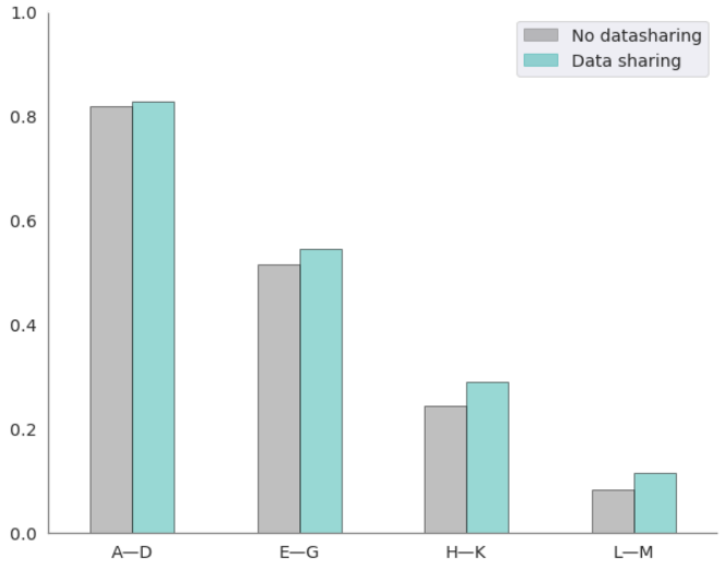
Figure 3: Age of applicants, measured monthly



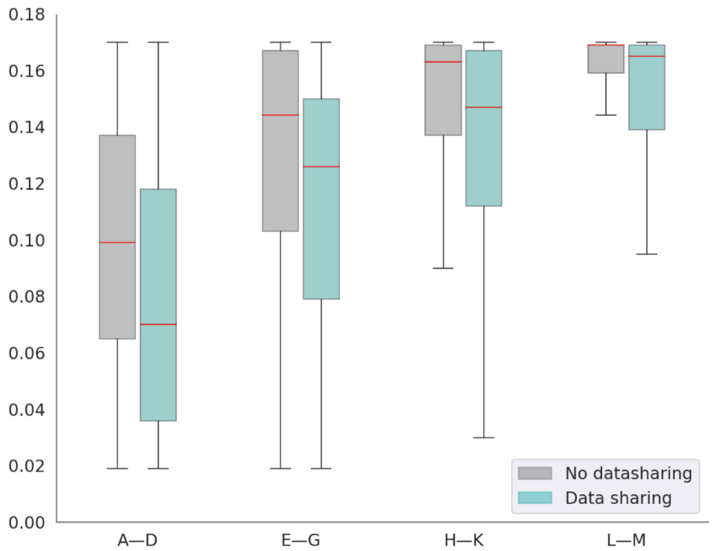
Note: This figure shows the inter-quartile range of applicant age. The sample period is from January 13, 2018, to May 22, 2022.

Figure 4

A. Loan approval rate by data sharing decision



B. Loan interest rate by data sharing decision



Note: Panel A displays the average loan approval rate, and panel B shows the inter-quartile range of interest rates. Green bars represent data sharing applicants, and gray bars represent non-sharing applicants across credit score groups from A–D (highest) to L–M (lowest).

A Additional Tables and Figures

Table A.1: **Descriptive statistics by data sharing decision**

Variable	Signup	No signup	p-value
Credit requested	12,841.07	13,963.36	0.00
Interest rate*	0.10	0.12	0.00
Platform score (max 7, min 1)	3.22	2.87	0.00
Credit score group (max 4, min 1)	3.06	3.13	0.00
Loan duration	52.90	55.73	0.00
Application accepted (D)	0.70	0.67	0.00
Bank account detail shared (D)	1.00	0.00	0.00
Age	34.19	38.53	0.00
Female (D)	0.33	0.35	0.00
Main earner (D)	0.63	0.62	0.00
No. current loan demand	1.56	1.33	0.00
No. past loan demand	1.28	1.02	0.00
Total income	2,235.39	2,365.18	0.00
Total expenses	744.41	715.11	0.00
Credit card holder (D)	0.78	0.63	0.00
Checking account holder (D)	0.97	0.94	0.00
Homeowner (D)	0.20	0.26	0.00
Car owner (D)	0.61	0.56	0.00

Notes: This table presents summary statistics separately by data sharing choice, *Signup*, and for those who opt out, *No signup*. (D) = dummy variable. The monetary unit in EUR. The sample period runs from January 13, 2018, to May 22, 2022. The final sample includes only one application per applicant. In the case of multiple applications, the initial application from each applicant is included. *conditional on loan approval.

Table A.2: **Descriptive statistics by access channels**

	Access channel				
Variable	Directly via homepage	Repeat Borrower	Price comp. website	Broker	Bank
Credit requested	8,232.91	11,379.20	15,049.82	11,700.52	4,756.91
Interest rate*	0.12	0.09	0.11	0.13	0.13
Platform score (max 7, min 1)	2.52	4.63	3.11	1.85	1.56
Credit score group (max 4, min 1)	2.85	3.15	3.22	2.84	2.47
Loan duration	27.91	53.62	56.79	62.94	68.52
Application accepted (D)	0.61	0.97	0.73	0.40	0.31
Bank account detail shared (D)	0.11	0.17	0.08	0.04	0.03
Age	34.79	43.27	38.75	37.58	29.51
Female (D)	0.39	0.40	0.34	0.38	0.22
Married (D)	0.29	0.42	0.41	0.36	0.19
Main earner (D)	0.12	0.32	0.66	0.70	0.87
No. current loan demand	1.20	1.84	1.39	1.23	0.73
No. past loan demand	1.02	1.81	1.03	1.12	0.53
Total income	2,125.52	2,508.09	2,420.04	2,087.69	2,342.38
Total expenses	862.46	1,107.86	719.10	542.15	992.08
Credit card holder (D)	0.42	0.65	0.70	0.40	0.93
Checking account holder (D)	0.87	0.98	0.96	0.82	0.99
Homeowner (D)	0.16	0.30	0.28	0.16	0.16
Car owner (D)	0.51	0.68	0.62	0.28	0.38

Notes: This table presents descriptive statistics on borrower and loan characteristics by access channel. (D) = Dummy variable. The monetary unit is EUR. The sample period runs from January 13, 2018, to May 22, 2022. The final sample includes only one application per borrower. In the case of multiple applications, the initial application from each borrower is included. *conditional on loan approval.

Table A.3: **Matched variables and matching results**

A. Sample to estimate the effect of data sharing on loan approval rates (equation 2)

	Mean treated	Mean control	Mean p-value difference
Age	33.778	33.762	0.654
Credit score	3.0552	3.0579	0.306
Income decile	5.3476	5.3476	0.997
Access channel		——— exact matching ———	
Application year		——— exact matching ———	

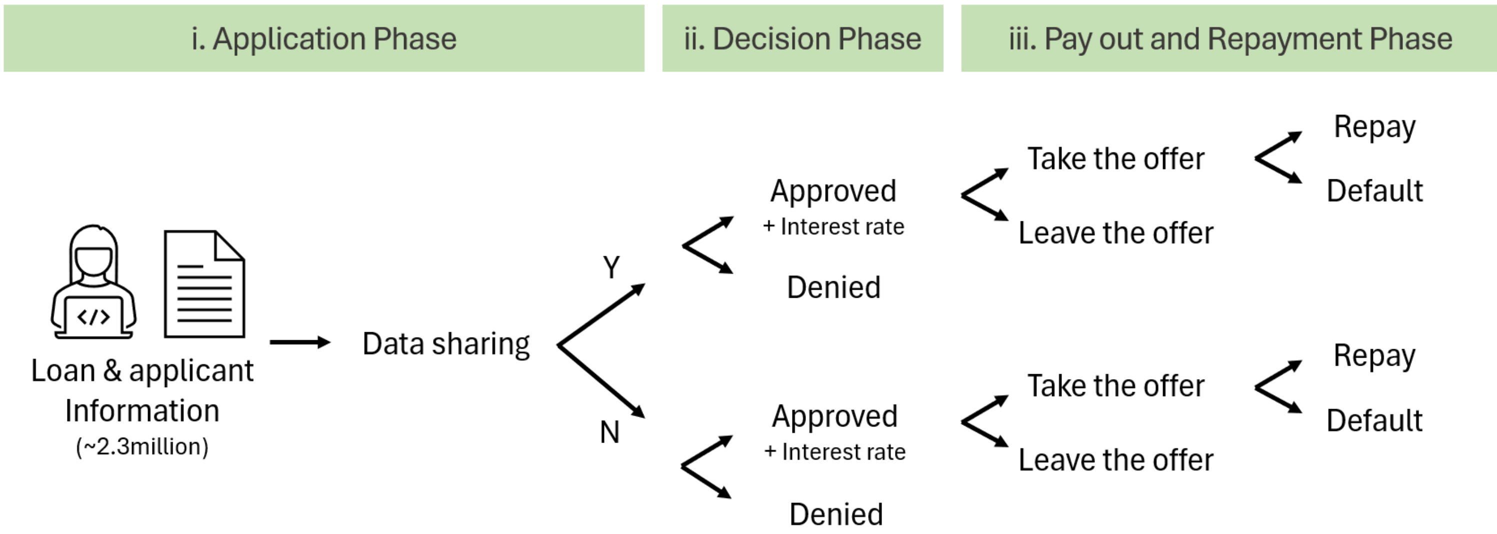
Notes: This table shows t-tests for the null hypothesis of equal means for both data sharing and non-sharing groups. This sample is used to compute the effect of data sharing on the probability of loan approval (equation 2). Each of the 188,453 applicants who shared data is matched one-to-one using age, credit score, income decile, access channel, and loan application year to create a control group of those who did not share data but is observably similar. Propensity score matching is used for age, credit score, and income decile, and exact matching is used for access channel and loan application year. The final sample includes 376,852 loan applications from 375,852 unique applicants.

B. Sample to estimate the effect of data sharing on interest rates (equation 3)

	Mean treated	Mean control	Mean p-value difference
Age	36.496	36.477	0.662
Credit score	3.3081	3.3081	1.000
Income decile	5.8796	5.8908	0.331
Access channel		——— exact matching ———	
Application year		——— exact matching ———	

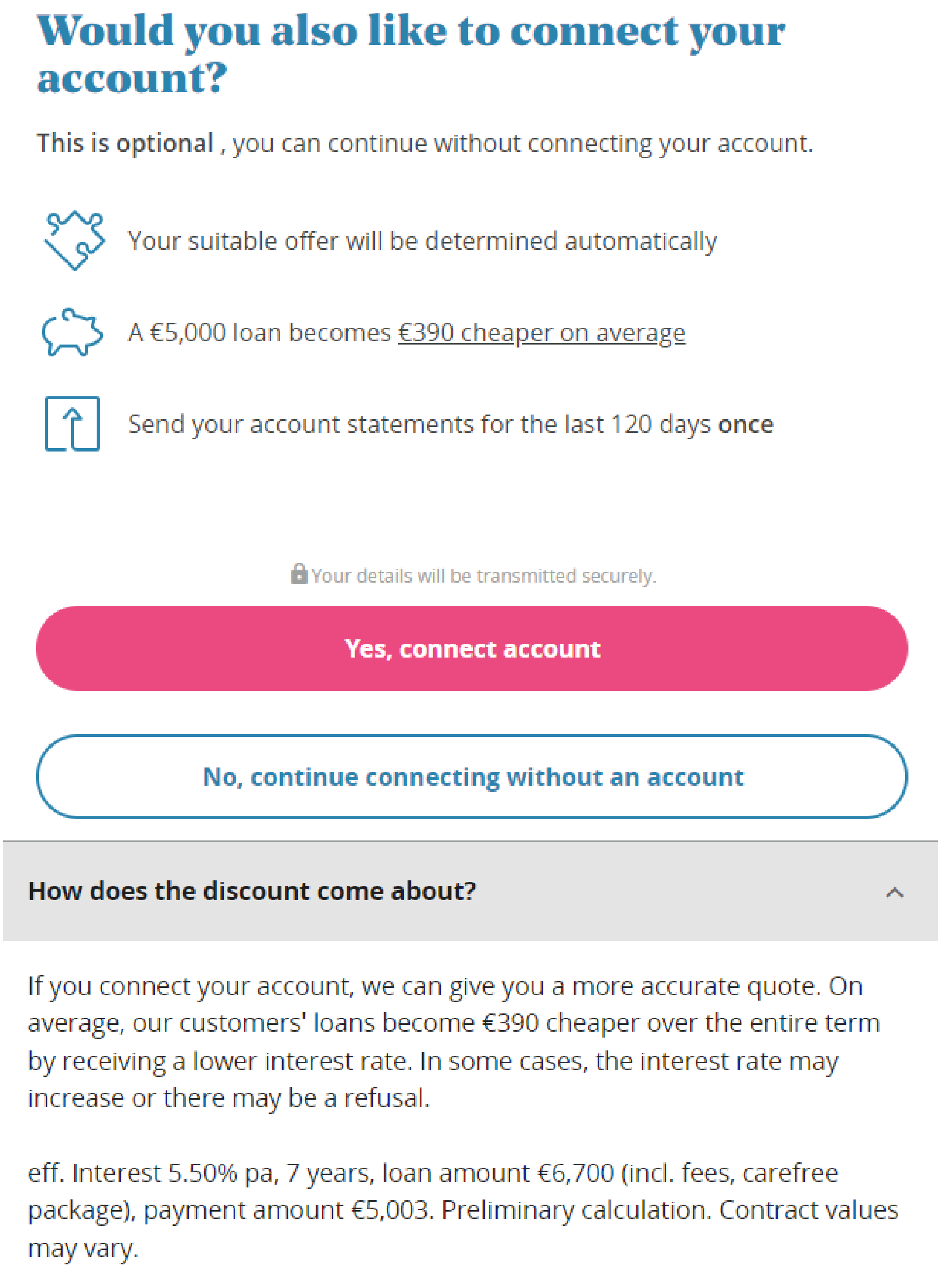
Notes: This table shows t-tests for the null hypothesis of equal means for both both data sharing and non-sharing groups. This sample is used to compute the effect of data sharing on the interest rate (equation 3). Interest rates are revealed only for successful loan applications. Each of the 125,889 *approved* applicants is matched one-to-one with *approved* applicants (to ensure interest rate information is available for all units), using age, credit score, income decile, access channel, and loan application year to create a control group of those who did not share data but is observably similar. Propensity score matching is for age, credit score, and income decile and exact matching is used for access channel and loan application year. The final sample includes 249,240 loan applications from 249,240 unique loan applicants.

Figure A.1: Loan application procedure



Notes: This figure depicts the loan application procedure on the platform.

Figure A.2: Data sharing during the application



Notes: This figure shows the exact manner in which data is shared during loan applications. Loan applicants are also supplied with information regarding data usage, and data security.

Figure A.2: Data sharing during the application (continued)

How does the discount come about?

How will my loan get cheaper?

How are my bank statements transmitted?

Is the transmission of my bank statements secure?

The connection is encrypted, we have no access to your access data and your account. You finally confirm the transmission via 2-factor authentication.

What happens if I don't connect my account?

Why am I being asked for bank statements?

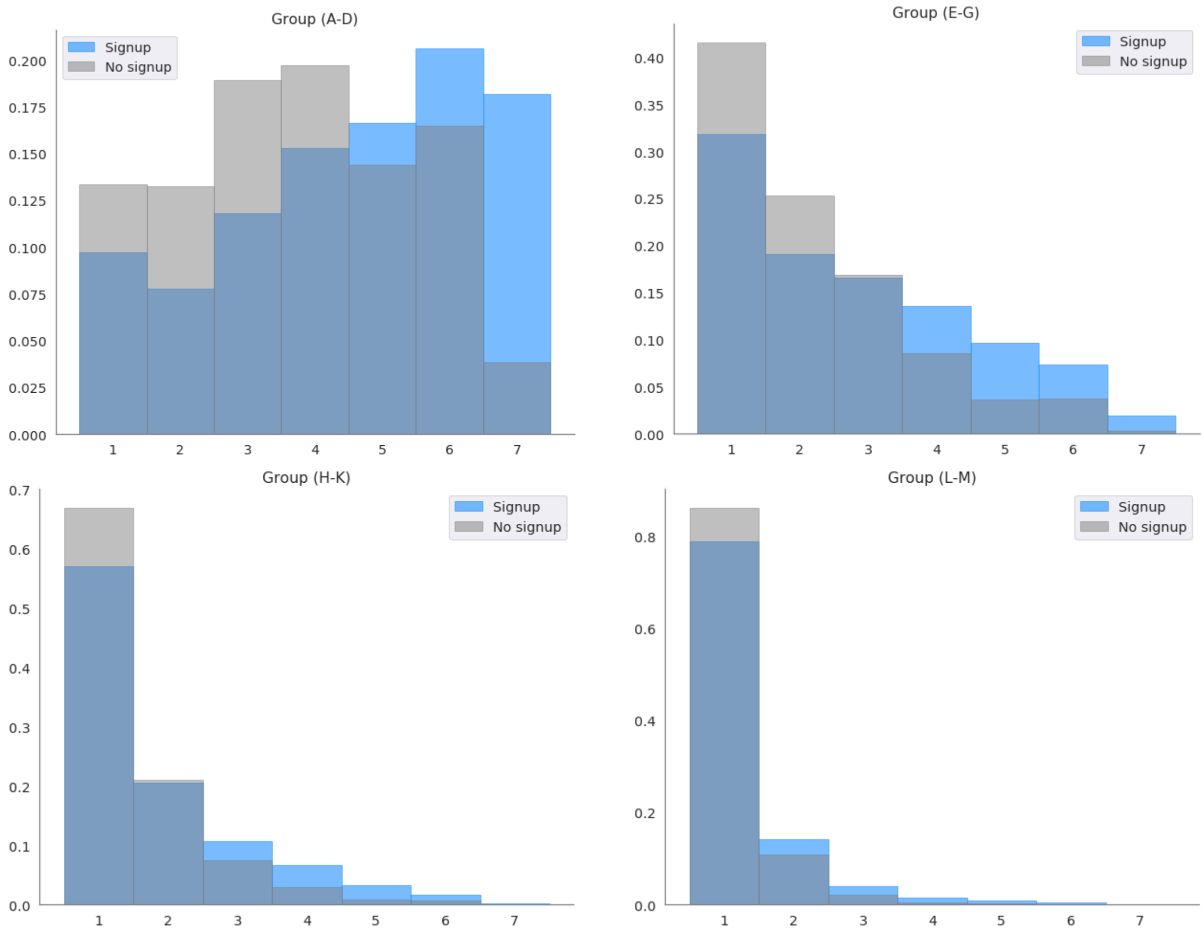
Income and expenses are automatically recognized and analyzed based on account statements. This allows the credit default risk to be assessed more precisely and a suitable offer to be made available. Your offer can improve or deteriorate as a result, and this may also lead to your loan request being rejected.

What do I do if I can't find my bank?

What do I do if I don't have online banking?

Notes: This figure shows the exact manner in which data is shared during loan applications. Loan applicants are also supplied with information regarding data usage, and data security.

Figure A.3: Distribution of platform-provided credit score by signup decision (using the matched sample)



Note: These figures depict the range of scores assigned by the platform (x-axis) after the application is completed, with 7 the highest and 1 the lowest and indicating rejection. Applicants choose to share their data prior to obtaining the loan approval decision, platform score, and interest rate. The y-axis measures the share of applicants.

B Empirical Analysis: Impact on Non-Disclosure in Loan Approval

A key question emerges regarding the equilibrium effects for those who decide against sharing data. The issue is whether lack of disclosure could be seen as a signal of subpar borrower quality, potentially leading to negative consequences for these individuals in the credit market.

This concept aligns with Akerlof's 'market for lemons' theory (Akerlof 1970), where asymmetric information contributes to uncertainty about quality. In Akerlof's framework, as the higher-quality goods (or 'non-lemons') leave the market (in the open banking setting, they would choose to disclose instead of existing the market), the chance that the remaining goods are of lower quality rises. In a similar vein, in the credit market, as more applicants, presumably those with better credit profiles, choose to share their data, those who do not might be increasingly viewed as higher risks or 'lemons.' This situation can lead to a cycle where the act of withholding data itself becomes a bad signal.

To empirically assess these dynamics, my methodology involved two key steps. 1) *Grouping Applicants Based on Observable Characteristics*: applicants were categorized into pools based on similar observable characteristics using quintiles to ensure comparability within each pool to assess the impact of non-data sharing, 2) *Computing Data Sharing Share within Pools*: For each pool, I calculated the proportion of applicants disclosing their transaction data. The focus here was to examine if an increase in this proportion within a pool adversely affects those who do not disclose their data with regards to loan approval rates. The analysis leverages the variation in data sharing over time, as shown in 2, to empirically test the hypothesis whether an increase in data sharing within a pool negatively impacts the loan approval rates for those who do not share data

The findings suggest that an increase in data sharing within a pool is indeed associated with a decreased probability of loan approval for non-disclosers. Specifically, a 10 percentage point increase in the share of data disclosure leads to a 0.1 percentage point decrease in loan approval probability for those who do not share. While statistically significant, so far the economic impact of this finding is modest. These results suggest the emergence of a partial separating equilibrium in the credit market. In an environment where the cost of data sharing (such as concerns for data misuse, and privacy concerns) are non-trivial, the decision not to disclose cannot be simplistically attributed to poor borrower quality. As shown by He, Huang, and Zhou 2023, the presence of privacy-conscious borrowers could mitigate the potential perverse effect of open banking (a negative externality on non-disclosure). Therefore, this paper empirically highlights the need for a nuanced understanding of data sharing behavior and its implications in the credit market, particularly in the context of evolving norms and practices around financial data privacy.

C Heckman's two-stage correction to address selection bias

Let the loan approval and interest rate functions be given by

$$L_i^* = Z_i'\gamma + \epsilon_i,$$

$$r_i = X_i'\beta + u_i.$$

First, I begin by introducing the basic Heckman model in a first stage and estimate the probability of being accepted for all applicants,

$$\begin{aligned} Prob(L_i^* > 0|Z) &= Prob(\epsilon_i > -Z_i'\gamma) \\ &= \Phi(Z_i\gamma), \end{aligned}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function with the variable of ϵ normalized to one. Interest rates are observed for those whose $L_i^* > 0$ so that the expected interest rate of a borrower is given by

$$\begin{aligned} E(r_i|L_i^* > 0, Z) &= X_i'\beta + E(u_i|\epsilon_i > -Z_i'\gamma) \\ &= X_i'\beta + \theta\lambda_i, \end{aligned}$$

where $\theta = \rho\sigma_u, \lambda_i = \frac{\phi(Z_i'\gamma)}{\Phi(Z_i'\gamma)}$, and $\phi(\cdot)$ is the standard normal density function. In the second stage, the interest rate equation for those who are accepted can then be expressed as

$$r_i|L_i^* > 0 = X_i'\beta + \theta\hat{\lambda}_i + e_i,$$

where $\theta\hat{\lambda}_i = \rho\sigma_u\hat{\lambda}_i$ represents the correction term. Here, ρ is the correlation between the unobserved determinants of the probability of being accepted ϵ and unobserved determinants of interest rate u, σ_u is the standard deviation of u, and $\hat{\lambda}$ is the inverse Mills ratio evaluated at $Z_i\gamma$.

D Additional robustness checks

D.1 Data sharing and borrower type: Using platform scores

Given the restricted sample size in Section 4.4 due to the limited availability of the loan outcome variable (*Default*), I conduct an additional analysis regarding the association between data sharing and borrower type using the platform score, which is the credit risk computed by the platform and incorporates the information derived from the shared transaction data. Therefore, the platform score captures traits that are unobservable ex ante but still relevant for credit risk.

[Figure A.3]

First, the distribution of platform-provided scores for each credit score group is shown in Figure A.3. If applicants who disclose data are of a good type conditional on credit score, I expect to see a rightward shift of the distribution for those who share because the platform score is provided after data sharing. The critical assumption is that the signup and no-signup population have ex ante an identical distribution. Thus, I use the matched sample. A quick look at the graphs indicates that the distribution of the platform score shifts toward the right.

Empirically, I regress the data sharing decision *Signup*, on a dummy variable *Good type*, which takes a value of one for platform scores three through seven and zero for platform score two. Platform score one (rejected) is excluded. Assuming both the signup and no-signup population ex ante have an identical distribution, and if the decision to signup was random in terms of unobserved borrower type, it is expected that there will be no significant shift in the distribution. I estimate this for each credit score group. Table D.1 shows that for the highest credit score group, on average, it is 16 percentage points more likely that the good type signs up, and the effect is even larger for the lower credit score groups: 20.6 and 19.9 percentage points for (E–G) and (H–K), respectively. The magnitude, however, is attenuated for the lowest credit score group, with only an 8.7 percentage point increase. The results are qualitatively consistent with the main analysis using ex post defaults.

[Table D.1]

There are, however, limitations to using platform scores as proxies for borrower types. For instance, the data sharing decision itself may lead to a better score regardless of borrower type and the information contained in the data. Thus, there is a possibility that the rightward shift of the distribution is partially driven by the signup decision itself rather than positive information content that suggests a good borrower type. Importantly, even with access to such granular payment data, the borrower type will only be known ex post.

Table D.1: **Data sharing decisions and the borrower type using platform scores**

	DV = 1 if data is shared			
	Matched sample			
Credit score group	(A–D)	(E–G)	(H–K)	(L–M)
Goodtype (=1 if platform score 7-3)	0.160***	0.206***	0.199***	0.087**
	(0.006)	(0.004)	(0.007)	(0.021)
Controls	Y	Y	Y	Y
Cluster (region-year)	Y	Y	Y	Y
N	110,968	107,012	27,950	3,148
Pseudo R2	0.0306	0.0362	0.0322	0.0193

Notes: This table shows the probability of data sharing among *Goodtype* borrowers (a dummy variable equal to one for platform scores from three through seven and zero for platform score two). A probit model with the matched sample is used for the analysis. Each column represents a risk group with (A–D) the highest and (L–M) the lowest. Each of the 124,539 loan applicants who shared data is matched one-to-one using age, credit score, income decile, access channel, and loan application year to create a control group of those who did not share data but is observably similar. Propensity score matching is used for age, credit score, and income decile, and exact matching is used for access channel and loan application year. The final sample includes 249,078 loan applications from 249,078 unique applicants. Control variables include age, income decile, loan amount, loan duration, female (dummy), married (dummy), main earner (dummy), number of current and past loans, homeowner (dummy), car owner (dummy), and access channel (categorical variable).

D.2 Selection on unobserved variables: Rosenbaum sensitivity analysis

To further address hidden bias from unobserved variables that may affect both the data sharing decision and the outcome variable, I follow the method proposed by Rosenbaum 2002 and test the size of the quantitative deviation from a random assignment that would result in a statistically insignificant effect of data sharing. It is a useful tool to test the sensitivity of causal inferences by allowing researchers to quantify how severe unmeasured confounding variables must be between the treated and control units in order to nullify the effect of data sharing. Rosenbaum bound explicitly allow the odds of data sharing to vary between the treated and control individuals by a parameter, $\Gamma \geq 1$, when the two groups have similar observable characteristics $X_t = X_c$; that is,

$$\frac{1}{\Gamma} \quad \leq \quad \frac{\dfrac{\pi_t}{(1-\pi_t)}}{\dfrac{\pi_c}{(1-\pi_c)}} \quad \leq \quad \Gamma \qquad \text{when} \quad X_t = X_c, \tag{4}$$

where $\pi_i = Pr(D_i = 1|X_i) = F(\beta x_i + \gamma u_i)$ is the probability of data sharing that can be expressed is a logistic function F, and x_i and u_i are the observable and unobservable variables, respectively. The i's odds of data sharing are $\frac{\pi_i}{1-\pi_i} = e^{\beta x_i + \gamma u_i}$. If $\Gamma = 1$, $\pi_t = \pi_c$, this means the odds of data sharing are the same for the data sharing and non-sharing groups, who share similar observable characteristics. By setting the value of Γ to be greater than one, the degree of hidden bias can be varied. If $\Gamma = 2$, the data sharing group is twice as likely as the control group to share data due to unobservable differences.

I first match individuals who share data on all observable characteristics to create a control group and examine the bounds at which the effect of data sharing is no longer significant. Table D.2 reports the bounds parameter Γ. The statistically significant effect of data sharing on the extensive margin will be challenged only if the unobserved biased selection into sharing were so high to cause the odds ratio of data sharing to differ between the two groups by around five times for the highest credit rating bracket (A–D). While the results for the second-highest credit score group (E–G) are less pronounced, the selection on unobservables would still have to be more than 50% as high. For the rest of the groups, the effect is statistically significant at all levels of the sensitivity parameter gamma. This means that even if there is a large amount of hidden bias due to unobserved covariates (i.e., a 20 times larger odds ratio), data sharing still has a statistically significant effect. Overall, this evidence suggests that selection on unobservables would have to be very large to eliminate the effects of data sharing.

Table D.2: **Rosenbaum bounds sensitivity analysis**

	Credit score groups			
	(A–D)	(E–G)	(H–K)	(L–M)
$\Gamma_{p>.01}$	4.98	1.53	20^{+}	20^{+}
$\Gamma_{p>.05}$	5.04	1.54	20^{+}	20^{+}
$\Gamma_{p>.10}$	5.08	1.55	20^{+}	20^{+}

Notes: This table shows how much higher the odds of data sharing based on unobservables would need to be for the data sharing group compared to the non-sharing group such that the effect of data sharing is no longer significant at the 1%, 5%, and 10% level. Each of the loan applicants who shared data is matched one-to-one to create a control group of those who did not share data using all observable variables.