Open Finance, Privacy, Trust and Financial Inclusion: Evidence from a Randomized Experiment in Brazil*

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Abstract

We explore the determinants of open banking adoption among microentrepreneurs, and how adoption translates into financial inclusion. We implement a randomized experiment where targeted information on open banking (called 'Open Finance' in our context) was provided to Brazilian micro firms. We find the intervention to increase open banking adoption by more than 40% compared with the control group. The effects are larger for younger, more educated owners, and those with multiple business accounts — indicating that financial sophistication plays a key role for adoption. We also find that the treatment group shares data to a higher extent than the control group both with their main bank and also with other banks with weaker relationships. Concerns for privacy and trust towards institutions significantly affect both adoption and data sharing. Analysis of administrative data from the Central Bank of Brazil reveals that adoption increases the extent of instant payments ('Pix'), both in terms of number of transactions and average amount, at least in the short term.

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1 Introduction

Open banking initiatives are increasingly being implemented by regulators around the world (He et al., 2023; Babina et al., 2025; Nam, 2023). Notwithstanding their potential to improve credit access for both consumers and micro, small and medium-sized enterprises (MSMEs), the take up of open banking initiatives remains far from universal. In the United Kingdom, one of the earliest promoters of open banking since 2016, only one in five consumers and SMEs have adopted it (Open Banking Limited, 2025). In Brazil, although open banking (called 'Open Finance') incorporates a broader spectrum of financial services, such as insurance and pension funds that have the potential to facilitate broader financial inclusion, administrative data suggest that adoption rates may be even lower: at most 20% among individuals and less than 2% among firms (Open Finance Brasil Association, 2025).

Low take-up numbers of open banking are even more puzzling in light of the emergence of digital payment methods and the entry of fintech (Puri et al., 2017; Berg et al., 2020; Higgins, 2024; Mariani et al., 2025), which offer customers the unprecedented opportunity to share real-time transaction data across financial institutions to obtain tailored financial services and better credit terms (Alok et al., 2025; Babina et al., 2025).

In this paper, we report findings from a randomized intervention that aims to to increase the take up of Open Finance among Brazilian microentrepreneurs. We combine two rounds of primary data collection with administrative data from the Central Bank of Brazil (BCB) to study average treatment effects of Open Finance adoption, individual- and business-level heterogeneity, and downstream impacts on financial access, including digital payments and credit.

Our main result is that a short informational video highlighting the benefits of Open Finance raises adoption by about 7 percentage points relative to the control group ($\approx 42\%$ of the control-group mean at follow-up). The effect is larger for younger and more educated microentrepreneurs, as well as for respondents who report stronger concerns about their personal data privacy. In Brazil, it is common for entrepreneurs to use their personal bank accounts for business purposes. Consistent with a financial sophistication channel, treatment effects are also larger among owners with two or more business accounts, indicating the importance of good business management practices. Overall, the evidence points to digital literacy, financial sophistication, and privacy concerns as key drivers of Open Finance take up once information about data security and benefits is provided.

We then look at how Open Finance adoption translates into effects on real outcomes leveraging administrative data from BCB: two months after the intervention, we find evidence that microentrepreneurs assigned to the treatment group perform a significantly higher number of digital payments via Pix in their business account; we also find evidence that the average value of these digital payments is significantly higher in the treatment group vs. the control group. These results suggest that the benefits of using Pix increased as microentrepreneurs join Open Finance.[1]

Our experiment involved 1,151 microentrepreneurs running small storefront businesses in the retail and service sectors in the Brazilian state of Espírito Santo. Between April and July 2025, we administered a short in-person baseline survey to each individual. At the end of the survey, we showed a video to both the treatment and control group covering Pix usage, financial organization, and the benefits of having separate business accounts. Microentrepreneurs assigned to the treatment group saw a video that contained an additional segment describing the benefits of Open Finance. After an average of 16 days, we re-contacted each microentrepreneur via WhatsApp to administer a short follow-up survey to measure adoption of Open Finance as well as self-reported changes in the demand for financial services and products. Additionally, at both baseline and follow-up, we asked respondents a set of questions to learn which banks they had accounts with – these questions were then used to understand whether increased knowledge about Open Finance may affect microentrepreneurs' banking relationships.

Our findings are consistent with information-based models of technology adoption (e.g., Foster and Rosenzweig, 1995; Conley and Udry, 2010), where reducing information frictions about benefits increases take-up. Yet, compared to more "traditional" technologies, the adoption of financial technologies suffers from additional barriers – privacy concerns (Choi et al., 2025; Doerr et al., 2023; Tang, 2023), lack of digital and/or financial literacy, and trust towards institutions and banks (Okat et al., 2025), among others. At the same time, open banking initiatives create a signaling game whereby borrowers' willingness to share their bank transaction data conveys information about their creditworthiness (He et al., 2023; Babina et al., 2025). It follows that high-quality borrowers have stronger incentives to share data because better screening technology helps lenders identify them as low-risk.

The richness of our data allows us to test the above hypotheses and to uncover several novel

[1] As discussed in our Pre-Analysis Plan, we will additionally study whether the adoption of Open Finance leads to improved access to credit by looking at treatment effects on credit volumes and credit limits.

and stylised facts on Open Finance. First, in line with country-level take-up rates in Brazil, the adoption of Open Finance at baseline is low: approximately 10% of our sample knew what Open Finance was, and less than 8% reported having adopted it. Second, we show that the provision of generic information on the latest innovations in financial inclusion (including fintech, digital payments, and their role in promoting credit access) may create appetite for Open Finance: at the follow up, the rate of Open Finance adoption in the control group had almost doubled. However, it is the provision of specific information on Open Finance, and its potential to enable receipt of tailored financial services and products once information is shared among financial institutions, that moves the needle on adoption. Additionally, we find that the treatment effects are more pronounced among respondents with high privacy concerns, indicating that the video was effective at addressing a salient barrier – fears of data misuse by banks.

One key feature of Open Finance is that adopters can choose which banks can access additional information from other financial institutions. Our newly assembled dataset allows us to precisely observe microentreprenerus' behavior with respect to this. Firstly, we look at whether firms share information with their main bank (the ones handling most of their payments) or with a different bank (that might use the information to offer new products). We find that firms share data predominantly with their main bank, thereby limiting data sharing with banks where they have had fewer transactions. We also find that the treatment increases data sharing across the spectrum of both digital and more traditional banks. These results indicate that lowering information frictions expands data sharing both along the incumbent margin and towards alternative financial providers, leading to significant shifts towards digital financial institutions.

Secondly, by further looking into heterogeneous treatment effects, we find that individuals in the treatment group who at the onset of the intervention place high value in having control of their data are not only more likely to share data with their main bank, but also with other banks, as compared with the control group. This result suggests that privacy salience may expand Open Finance adoption towards non-main banks.

On the contrary, we do not find that trust towards the financial system or greater risk tolerance trigger Open Finance adoption on average. We do find, however, that treated microentrepreneurs with high trust in banks, as well as those with higher risk tolerance, are more likely to share data with non-main banks vs. the control group. Taken together, these findings suggest that privacy concerns, trust and risk tolerance differently affect individuals' data sharing

when Open Finance is available.

Our paper adds to four distinct streams of literature. The first is the recent literature that studies the diffusion of open banking initiatives around the world (He et al., 2023; Babina et al., 2025; Nam, 2023). We show that social attitudes towards fintech and privacy significantly affect the adoption of Open Finance. Additionally, we generate evidence on how heterogeneities in privacy concerns, trust, and other characteristics like risk tolerance shape the type of financial institutions MSMEs are most likely to share their data with.

The second stream of literature we contribute to is that on fintech adoption. We show that reducing information and salience frictions around Open Finance can increase take-up among microentrepreneurs, and that who chooses to adopt —and with which counterpart they share data — depends on privacy salience, risk tolerance, and institutional trust. In contrast to settings where network complementarities and learning dynamics slow diffusion, we document both the reallocation of data sharing away from large incumbents and towards digital banks, complementing the literature on fintechs' comparative advantage in using transaction data (Chioda et al., 2024). Our results add to work on payment network externalities and adoption under shocks (Higgins, 2024; Crouzet et al., 2023; Sampaio and Ornelas, 2024), learning about new financial technologies (Breza et al., 2020), the role of cash and cashless transactions (Alvarez et al., 2021; Argente et al., 2025; Ouyang, 2021), and fintech lending and digital banking growth (Puri et al., 2017; Berg et al., 2022; Mariani et al., 2025).

Thirdly, our paper broadly speaks to the literature on financial inclusion for vulnerable individuals in the spirit of Burgess and Pande (2005); Banerjee et al. (2013); Barboni et al. (2021). It does so by focusing on Brazil, a country that throughout the years has introduced several policies to tackle poverty (Van Doornik et al., 2024; Fonseca and Van Doornik, 2022; Fonseca and Matray, 2024) and who recently has experienced a radical digital transformation that holds the potential to lead to a structural change in the economy, as Dubey and Purnanandam (2023) and Alok et al. (2025) have shown for India.

Finally, we contribute to literature that finds that financial innovations are most likely to be taken up by financially sophisticated segments of the population (Barboni and Agarwal, 2023; Beaman et al., 2023; Bryan et al., 2024). Specifically, we show that information about Open Finance helps technology savvy (young and more educated) individuals and people with privacy concerns to overcome adoption barriers. While this goes beyond the scope of our paper, our results suggest that the diffusion of innovations like Open Finance may exacerbate inequalities,

as shown for example by Jiang et al. (2022) and Cespedes et al. (2024).

2 Context and Experimental Design

Open banking consists of a series of data-sharing initiatives typically regulated by Central Banks that allow individuals and firms to securely share their financial information, such as transaction history, investments, and credit profiles with other authorized financial institutions, always with explicit customer consent. As of 2024, 95 jurisdictions have adopted open banking initiatives to some extent (Cambridge Centre for Alternative Finance, 2024).

Since 2010, BCB has had financial inclusion as a key strategic objective (Banco Central do Brasil, 2010; Alliance for Financial Inclusion, 2018). The BCB's current work agenda (*Agenda BC#*) focuses on inclusion, competitiveness, transparency, education, sustainability, and excellence. Within this framework, Brazil's financial landscape has undergone a profound transformation over the past five years, driven by the widespread adoption of digital payments—particularly Pix—and the rollout of Open Finance.

2.1 Open Finance in Brazil

In May 2020, the Central Bank of Brazil introduced Open Finance with the objective of encouraging innovation; promoting competition; increasing the efficiency of the financial and payment systems; and promoting financial inclusion.[2] Its implementation started in 2021, with a continuous roll-out of new features.[3] As with other open banking initiatives, Open Finance's core principle is to give customers greater control over their financial data, allowing them to share it securely with other financial institutions for better access to services such as loans and advice, and more tailored credit terms.

To initiate sharing, the customer starts in the app/website of the institution that will receive the data (the "data recipient"). They then select the data types they would like to share, and from which source institution (the "data holder"), after which they are redirected to the holder to authenticate and approve access. Customers must provide consent for each account individually.[4] Once consent is in place, the chosen recipient may use the shared data to deliver services

[2] https://www.bcb.gov.br/content/config/Documents/Open_Banking_CMN_BCB_Joint_Resolution_1_2020.pdf

[3] Open Finance is a broad initiative not just targeted at individuals and businesses, but also designed to extend data interoperability in other domains like insurance, investments, and supplemental pension schemes, for example

[4] Consents are revocable at any time through either the data recipient's or the data holder's channel, and they do not grant blanket access to "other institutions" — only the specific recipient named in the consent can access the approved data.

such as credit proposals, financial management tools, or investment recommendations.

The ecosystem operates through standardized Application Programming Interfaces (APIs) and participation from major financial institutions is mandatory.[5] As of December 2024, financial institutions had received 62 million active data-sharing consents from individuals and businesses (Open Finance Brasil Association, 2025). In the same year, 102 billion API calls were executed by financial institutions. Although this means that Brazil leads open-banking in terms of absolute numbers, overall adoption is low. Less than 20% of Brazilians shared their data via Open Finance, and adoption rates for firms is even lower, with a participation rate of less than 2% (Open Finance Brasil Association, 2025).

2.2 Pix

In the same year Open Finance was launched, BCB also introduced Pix, a real-time payment system. Pix is instant, alias-based, available 24/7, and free for individuals and for many businesses[6], requiring only a bank or payment institution account and internet access. Pix has become an essential tool for both individuals and businesses, processing over 63 billion transactions in 2024, and becoming nearly universal. It has increasingly replaced both cash and card-based transactions.

One of the key benefits of systems like Pix is their ability to generate "hard information" about users' financial behaviors, which is valuable to the financial institutions that can access it. Unlike informal cash transactions, digital payments create a traceable record of financial activities that banks and other financial service providers can use to better assess creditworthiness and offer tailored financial products.

2.3 Experimental Design

We use a cluster-randomized controlled trial to evaluate whether a short, video-based information intervention could increase adoption of Open Finance – and other downstream, financial outcomes – among microentrepreneurs. Firms assigned to the control group watched a video that simply focused on the benefits of financial inclusion, while those assigned to the treatment group watched a longer version of the same video that also discussed the benefits of adopting

[5] API calls are a useful proxy for backend adoption in Open Finance. Each call represents a data-sharing request made between participating institutions. High API volumes would indicate strong institutional and technical uptake even if individual or firm-level adoption is still developing.

[6] Some businesses may need to pay small fees depending on the business size and bank

Open Finance, and data sharing across financial institutions more broadly (see Figure A1 for screenshots from both videos).

To evaluate impact, we conducted an in-person baseline survey followed by a WhatsApp-based follow-up survey. We also paired primary data with administrative data provided by BCB. Compensation was provided to all firms for participation in both surveys: a voucher worth approximately 70 BRL, or 13 USD for the baseline and a voucher work approximately 35 BRL, or 6.50 USD, for the followup.

Sampling: We used a two-step sampling strategy. First, we geolocated a set of microenterprises from the Brazil's Federal Revenue Service (*Receita Federal*). and visited each one. However, only a subset of firms could be reached, as many had moved or gone out of business.To ensure we met the target sample size, we then moved on to conducting on-street canvassing within predefined cluster boundaries and invited all newly observed firms to participate using the same eligibility criteria.

Due to the potential impact of peer effects through shared business networks or word-of-mouth, we clustered firms spatially prior to randomization. Clustering proceeded in three steps: (1) Geo-coding: All candidate firms were geo-referenced using address data from *Receita Federal*. (2) Spatial algorithm: A constrained k-means algorithm grouped firms into compact, non-overlapping clusters that respected administrative-boundary contiguity and a maximum radius. (3) Balancing checks: Cluster solutions were iteratively refined to minimise variance in baseline characteristics (sector mix, firm age, owner gender) across clusters.

The final design comprises 56 clusters with a mean size of approximately 21 firms, for a total sample size of 1,170 [7], as shown in Figure 1.

3 Conceptual Framework

The intervention we study is intended to provide microentrepreneurs with information about Open Finance. The experiment was motivated by the widespread evidence that individuals lack knowledge about the benefits of Open Finance: according to a 2024 survey conducted with 1,452 people across Brazil , 74% of respondents reported knowing nothing or almost nothing at all about Open Finance (Zetta Datafolha Institute, 2024). This study also revealed that this

[7] Final analyses include 1,151 firms as we had to drop some firms which were located outside the pre-defined clusters

lack of knowledge about Open Finance is more pronounced among low-income individuals, a group that typically has been excluded from formal financial markets. Moreover, the Zetta survey also found that only 12% of individuals had shared or tried to share data; this figure was also confirmed in our study sample, where we observe that only 10% of respondents know what Open Finance is at baseline.[8]

Building on a large and well-established literature showing that providing information significantly boosts technology adoption (e.g., Conley and Udry, 2010; Foster and Rosenzweig, 1995; Hanna et al., 2014; Duflo et al., 2011; Bold et al., 2017; Suri, 2011), we hypothesize that receiving information on the benefits of Open Finance should increase its adoption. This leads us to formulate the following hypothesis:

Hypothesis 1: Open Finance Adoption *Compared to the control group, microentrepreneurs in the treatment group should be more likely to adopt Open Finance when provided specific information about it.*

In contrast with more "traditional" technologies studied in the literature (e.g., fertilizers and crops), adopting financial technologies such as Open Finance—where consented data are shared through a regulator-managed digital infrastructure—can be hindered by distinct frictions. Privacy and data-control concerns may deter take-up (e.g., Choi et al., 2025; Doerr et al., 2023; Tang, 2023), while low levels of digital/financial literacy and low trust in financial institutions can further depress adoption (e.g., Okat et al., 2025). Guided by these considerations, we formulate the following hypotheses on heterogeneous treatment effects:

Hypothesis 2a: Financial Sophistication *All else equal, the information-provision treatment has a larger effect on more financially and digitally sophisticated individuals (e.g., those with higher education, younger age, multiple bank accounts, or greater baseline use of digital payments).*

Hypothesis 2b: Privacy Concerns *All else equal, the information-provision treatment has a larger effect on individuals who report stronger privacy concerns over their personal data, to the extent that clarifying consent, security, and revocation reduces perceived disclosure costs.*

[8]We asked the following question at baseline (translated from Portuguese): "There is an initiative by the Central Bank of Brazil called Open Finance. What do you think this initiative is about?" Answers were unprompted.

Hypothesis 2c: Trust in Financial Institutions *All else equal, the information-provision treatment has a smaller effect among individuals with low trust in the banking sector (and a larger effect among those with higher trust), because a one-shot informational intervention is less effective at shifting relational beliefs about counterpart institutions.*

Hypothesis 2d: Risk Tolerance *All else equal, the information-provision treatment has a larger effect among individuals with higher risk tolerance, consistent with greater willingness to experiment with new financial technologies and counterparties.*

Finally, following He et al. (2023) and Babina et al. (2025), open banking generates a signaling environment in which the act of consenting to share transaction histories helps screen borrowers. Because outside banks lack relationship data, the *marginal informational value* of a firm's history is higher to those banks than to the incumbent that already observes most transactions. As a result, high-quality firms anticipate greater returns from authorizing access for counterparties with weaker prior relationships—such as non-main banks and digital entrants that can translate new information into offers—thereby intensifying competition. In most Open Finance implementations, consent grants a standardized data feed rather than cherry-picked records, so strategic behavior operates primarily through *counterparty selection* (and timing) rather than selective disclosure of "only good" transactions. This motivates the following hypotheses:

Hypothesis 3: Data Sharing (Extensive Margin). *Relative to the control group, micro-entrepreneurs assigned to the treatment are more likely to authorize data sharing, with increases not only for the main (incumbent) bank but also for banks with which they have weaker prior relationships.*

Hypothesis 4: Strategic Counterparty Selection. *Conditional on adopting Open Finance, treated micro-entrepreneurs are more likely to direct sharing toward counterparties for whom the informational gain is largest and the likelihood of new offers is higher—namely, non-main banks and digital providers. This selection margin should be particularly pronounced for borrowers with greater willingness to experiment, and attenuated when trust in the banking sector is low.*

4 Data and Empirical Strategy

4.1 Data

To assess the effects of our intervention on Open Finance adoption as well as downstream impacts on financial access including digital payments via Pix and credit, we leverage the following sources of data.

Primary data. We collected two rounds of primary data with firms based in the state of Espírito Santo: an in-person baseline survey, and a WhatsApp-based follow-up survey, both administered by OppenSocial, a Brazil-based survey firm. The baseline took place from April to July 2025 and was completed by 1,151 microentrepreneurs. The baseline survey captured firms' knowledge and adoption of Open Finance, as well as their use of major payment methods, including Pix. We also gathered characteristics of the employer or owner responsible for payment decisions (gender, education, age) and detailed managerial practices (frequency of financial accounting, how supply orders are placed, and typical timing of supply purchases). Finally, the survey measured microentrepreneurs' trust in government and institutions, privacy concerns, and risk aversion. Table 1 presents the mean for the main characteristics in the control and treatment group: the two groups were on average balanced along the main characteristics, suggesting that the randomization worked well. In particular, Table 1 shows that roughly half of the business owners we interviewed are women; they are fairly educated, with 80% of them having completed at least middle school. The businesses we included in the study are quite small, having on average 1.4 employees in addition to the business owner. Interestingly, at baseline approximately 10% of respondents knew what Open Finance was, and about 8% had adopted it, this share being balanced across treatment and control.

The follow-up survey was conducted via WhatsApp on average sixteen days after the baseline. The follow-up survey was substantially shorter than the baseline survey and contained questions to assess whether respondents had adopted Open Finance, when the adoption occurred, and which banks were used for adopting Open Finance (i.e., whether they were digital or non-digital banks;[9] whether they were the respondent's main bank etc.). Although the follow up survey was administered relatively soon after baseline, the pick up rate was consid-

[9]Following Mariani et al. (2025), we define digital banks as financial institutions that do not have branches or, more generally, that rely exclusively on digital customer channels.

erably low: only 35% of the original sample (401 subjects) completed the follow-up.[10] Table A1 shows that attrition is balanced across treatment and control. Moreover, the baseline characteristics of borrowers who completed both the baseline and follow-up are on average similar to the full set of respondents we interviewed at baseline, suggesting that there are no baseline characteristics that predict whether a respondent could be re-contacted at follow up (Table A2).

Finally, both at baseline and at follow-up, we collected the firm's taxpayer identification number to link our survey data with administrative information from BCB.

Proprietary Secondary Data: This is a suite of datasets available from BCB. The first is a comprehensive firm-level list of transactions completed using Pix, credit card, debit card, and other payment methods. This includes the amount, date, and characteristics of payers and payees. The second is a comprehensive firm-level credit registry that allows us to measure impacts on credit access, including loan amounts and characteristics (e.g., maturity, interest rate), as well as measures of delinquency. As our sample includes informal firms as well as firms with informal practices[11], we also consider the flows and credit from firm's owners.

4.2 Empirical Strategy

We use the following specification to compute our main treatment effects:

$$Y_i = \beta T_i + \theta' X_i + \gamma_i + \epsilon_i \tag{1}$$

where Y_i is a dummy that takes the value of one if at follow up the respondent reports having adopted Open Finance and zero otherwise; T_i is a dummy that takes the value one if firm i is in the treatment group. X_i is a vector of controls for the respondent measured at baseline, γ_i is a set of individual fixed effects (e.g., location, economic activity, time of the survey), and ϵ_i is the error term. Standard errors are clustered at the geographical cluster level to account for our unit of randomization (Abadie et al., 2023). Our coefficient of interest is β, which captures the impact (Intent-to-Treat, ITT) of providing information on Open Finance adoption. Whenever possible, we estimate Equation (1) using an ANCOVA model. Additionally, we select controls

[10] Our survey completion rate is in line with studies with whatsapp-based follow up interviews, see for example Barboni et al. (2024) in the context of Venezuelan migrants in Colombia.

[11] In Brazil there is a type of firm called an individual microentrepreneur (MEI), which can have at maximum one employee and were conceived for self-employed workers or very small business. The cash flow from these firms typically flows through the owner's accounts.

using a Post-Double Selection Lasso (Belloni et al., 2014; Cilliers et al., 2024). In further analyses presented below, we estimate Equation 1 using Y_i as a dummy that is equal to one if the respondent reports having adopted Open Finance with either their main bank or other banks, and with either digital or traditional banks. In future analyses using BCB administrative data, we will also estimate a slightly different version of Equation 1 for digital payments, credit and interest rates at the firm-bank level.

5 Results

5.1 Impact on Open Finance Adoption

We first estimate Equation 1 using adoption of Open Finance at follow up as the dependent variable. Results are shown in Table 2. At follow up, we find that 17% of respondents in the control group report having adopted Open Finance – this is twice the adoption rate at baseline. In the treatment group, however, the adoption rate is significant higher by 7 percentage points (+42% of the control mean), as compared to the control group. The estimates remain significant and of the same magnitude when including various sets of controls, including baseline adoption rates (column 2 of Table 2), Lasso-selected controls (column 3), and a battery of fixed effects to control for city-, sector- and time- unobserved heterogeneity. At the bottom of each column of Table 2, we also report p-values obtained from randomization inference (RI), which are very similar to the cluster-robust p-values shown in the panel above.[12]

One natural question is whether the results in Table 2 are driven by information on Open Finance specifically, or by the general information on financial access seen by both the treatment and control firms. To test whether general information on financial access was perceived differently between treatment and control, we asked a series of questions during the follow-up survey to measure respondents' willingness to take up additional financial products like bank loans, business credit cards, personal credit cards, and microcredit, among others. Results are shown in Table A3. We do not observe significant differences across treatment and control in terms of demand for these products, indicating that the main effects observed in Table 2 are precisely driven by information on Open Finance.

All in all, results from Table 2 reveal that providing individuals with general information on

[12]Through RI, we assess the probability that the treatment effects observed could be drawn from 1,000 alternative random assignments (Gerber and Green, 2012; Heß, 2017).

financial inclusion and fintech can trigger adoption of Open Finance. However, the provision of specific information on the benefits of Open Finance significantly moves the needle on adoption, as was predicted in **Hypothesis 1**.

5.2 Individual-level Heterogeneity

Our conceptual framework discussed in Section 3 predicts that financially sophisticated individuals should be more likely to take up Open Finance since they face fewer barriers to adoption. To test this hypothesis, we estimate the following regression equation:

$$Y_i = \beta T_i + \theta' X_i + \delta T_i \times X_i + \epsilon_i \tag{2}$$

where Y_i is again the probability that firm i has adopted Open Finance at follow up, T_i is a dummy equal to one if the respondent was assigned to the treatment group, and X_i is the vector of microentrepreneurs' characteristics associated with financial sophistication (education, age, but also use of multiple bank accounts). We are particularly interested in the sign and significance of the δ coefficient.

We start by looking at heterogeneous treatment effects by microentrepreneurs' education, proxied by the likelihood they have completed at least primary education. Results are shown in Table 3. While more educated microentrepreneurs are not more likely to have adopted Open Finance at follow up, the coefficient of the interaction term between the treated dummy and education is positive and significant, and robust to a battery of controls and fixed effects. Results from the joint significance test at the bottom of each specification leads us to reject the hypothesis that the treatment has no effect on educated entrepreneurs – this is also confirmed by the RI p-values.

We look next at heterogeneity by age. As shown in Table 4, younger individuals – those below 35 years old – are significantly more likely to adopt Open Finance when shown the informational video. This result is again robust to a number of controls and fixed effects. Taken together, results from Table 3 and 4 suggest that treatment effects are more pronounced among tech-savvy, sophisticated microentrepreneurs.

We complement these results by looking at heterogeneity by the probability of having two or more accounts used specifically for business activities. In Brazil, it is common for entrepreneurs to use their personal bank accounts for business purposes. In the pilots preceding the interven-

tion, for example, we found that at least one in three microentrepreneurs did not have separate accounts for business and personal use, and they mostly used personal accounts for their business.[13] Lack of business accounts thus signals poor managerial skills and broadly low levels of financial sophistication. In this context, Table 5 shows that treatment effects are concentrated among microentrepreneurs who have two or more business accounts, which we consider an indicator of better business managerial practices. Furthermore, we also find suggestive evidence in Table 6 that microentrepreneurs who use Pix more frequently are more likely to adopt Open Finance.

In sum, results from Table 3, 4 and 5 confirm **Hypothesis 2a**: our intervention has a larger effect on more financially and digitally sophisticated microentrepreneurs.

5.3 Privacy Concerns, Trust and Risk Aversion

We further study heterogeneous treatment effects across three key dimensions of Open Finance and, broadly, fintech adoption. These include (a) the extent to which subjects value having control over their data, (b) trust towards the banking sector, and (c) risk aversion. We start by estimating Equation 2 using a baseline self-reported measure of concern over data control.[14] Results are shown in Table 7. We find that the coefficient of the interaction term, δ, is positive and significant, indicating that microentrepreneurs who feel having control over their data is important are more likely to adopt Open Finance in the treatment than in the control group. We interpret this finding as evidence that the video we showed to the treatment group was successful at highlighting how secure the data sharing protocols underlying Open Finance are, as predicted by **Hypothesis 2b**. Table 8 and 9 further show heterogeneous treatment effects by trust towards the banking sector and the microentrepreneurs' level of risk tolerance.[15] Although we observe that the adoption is concentrated among respondents with high trust in banking, results are noisy. Similarly, we do not see a clear pattern in terms of heterogeneous treatment effects by baseline risk-tolerance level. Hence, we conclude that our data do not fully support **Hypothesis 2c** and **Hypothesis 2d**.

[13] https://poverty-action.org/what-brazils-micro-and-small-businesses-reveal-about-future-digital-finance

[14] At baseline, we asked microentrepreneurs: *How important it is to you to have control over who accesses your personal information and how it is used?*. Answers ranged from 1: not important to 5: very important.

[15] At baseline, we asked: *Do you trust the banking system to securely manage your financial transactions?* Answers ranged from 1: I do not trust to 5: I trust a lot. Similarly, we asked: *Are you a person who is generally willing to take risks or do you try to avoid risks?* Answers again ranged from 1: not at all willing to take risks to 5: 'very willing to take risks'.

5.4 Data Sharing Choice Across Financial Providers

One key feature of Open Finance is that adopters can choose which banks can access additional information from other financial institutions. As discussed in our Conceptual Framework, whether users decide to share data and with whom depends on both the quality of the adopters and the strength of the relationships they have with banks.

The richness of our data allows us to study whether microentrepreneurs start sharing data in response to our intervention, and with which financial institutions. We first estimate Equation 1 with a set of outcomes measuring with which financial institutions respondents have shared their data (i.e., have adopted Open Finance) with at follow-up. Results are reported in Table 10. Specifically, Panel A shows results from estimating Equation 1 using a dummy as the dependent variable that takes the value of one if at follow up the respondent reports having shared their data with their main bank (i.e., the bank that handles most of their incoming payments) and zero otherwise. Panel B, on the other hand, shows results from estimating Equation 1 using a dummy as the dependent variable that takes the value of one if at follow up the respondent reports having shared their data with additional banks with whom they have weaker relationships. Taken together, results from Panel A and Panel B of Table 10 show that microentrepreneurs in the treatment group are significantly more likely to authorize information sharing with their main bank.

We then replicate the analysis shown in Table 10 distinguishing between digital and traditional (non-digital) banks. Results are shown in Table 11. We find that the treatment increases data sharing with both digital and more traditional banks: the ITT coefficient is positive and significant, and with similar magnitude, both in Panel A and Panel B. Taken together, results from Table 10 and Table 11 indicate that lowering information frictions expands data sharing both along the incumbent margin (main bank) and towards alternative financial providers, with significant shifts towards digital financial institutions. These findings support **Hypothesis 3**, which postulated that treated firms should be more likely to authorize data sharing across a broader spectrum of financial intermediaries.

Next, we examine whether these average treatment effects vary with respondents' characteristics. We focus again on the three baseline margins mentioned previously: privacy concerns, trust in the banking sector, and risk tolerance. For each of these characteristics, we estimate heterogeneous treatment effects in the spirit of Equation 2, with the dependent variable reflecting

Open Finance adoption with main versus non-main banks, as well as digital versus non-digital recipients of shared data. Respondents who value data control to a higher extent are more likely to share data in response to the treatment, both with their main bank and with a different bank (Table 12), indicating that privacy saliency may expand the range of financial institutions adopters may share data with.

Trust in banks and risk tolerance both have positive and significant heterogeneous treatment effects on data sharing with a non-main bank (Table 13 and Table 17). These results are consistent with a trust and willingness-to-experiment channel whereby users with higher trust and higher risk-tolerance extend sharing outside the status quo provider.

Finally, we also find differential treatment effects depending on whether the receiving banks are digital versus non-digital. The interaction term of the treatment with privacy concerns is stronger for sharing data with digital banks than sharing with traditional banks (Table 15). On the contrary, heterogeneous treatment effects by trust and risk tolerance for sharing data with digital versus non-digital banks are less conclusive (Table 16 and Table 17).

Overall, our results confirm the predictions of **Hypothesis 4**: By clarifying concerns about data control, our intervention relaxes privacy-related frictions and broadens the choice of financial intermediaries respondents intend to share data with (i.e., non-main and digital banks). This holds the potential to lead to improved credit access and better credit terms by expanding the set of financial institutions that can observe and underwrite firms' transaction histories.

5.5 Administrative Data

So far, our analysis has focused on Open Finance adoption and its determinants, both in terms of individual-level characteristics (financial sophistication, privacy concerns, trust in the banking system) and the type of banks adopters choose to share their data with (main versus non-main and digital versus non-digital). This analysis leverages primary data collected both at baseline and at follow up of our intervention.

As the next step, we use firms' tax codes ('CNPJ') and, when these are not available, firm owners' tax codes ('CPF'), to link our survey data with administrative data from BCB. Ultimately, we manage to match 98% of the firms.[16] Table 18 shows balance checks for the variables available in the BCB records, measured three months before the start of the intervention: these

[16]The number of firms we are able to match is 1,128. According to administrative data, 13 firms from our original sample report zero revenues from non-cash transactions and hence are excluded from BCB data.

variables include revenues from Pix transactions, as well as from debit and credit cards, and several measures of formal borrowing. Overall, our sample is fully balanced when we consider administrative data, confirming results from balance checks using survey data shown Table 1.

We now turn to study treatment effects using administrative data from the Central Bank of Brazil (BCB). Table 19 shows the impacts of Open Finance adoption on the number of Pix transactions made by the customer in the past 30 days in their business account. This outcome was measured in August 2025 for all customers, hence between one and three months from the follow up. We observe that, on average, customers in the control group have performed 110 Pix payments in the past 30 days. We estimate a Poisson Pseudo Maximum Likelihood (PPML) regression and find that microentrepreneurs in the treatment group perform between 27% and 37% significantly more Pix payments. We further explore treatment effects on Pix payments by looking at the average value of Pix transactions microentrepreneurs make on their business account. Results are shown in Table 20. We find substantial impacts of Open Finance adoption on the average amount of Pix payments, with the intervention almost doubling the average Pix payment value in treatment vs. control. All in all, results from Table 19 and Table 20 point to a significant increase in the use of Pix in treatment vis-à-vis control group. We interpret this finding as evidence that our video made the benefits of using digital payments more salient to customers, and hence led to a larger use of Pix.[17]

We further leverage BCB data to conduct two additional heterogeneity results, which are shown in Table 21 and 22: treatment effects are concentrated among microentrepreneurs that have two or more business accounts (confirming results from Table 5) as well as among those that have any outstanding credit from their business account. Findings from Table 21 and 22 further confirm the prediction made in **Hypothesis 2a** about the role of financial sophistication in driving the adoption of Open Finance.

6 Conclusion

We conduct the first randomized experiment to boost adoption rates of open banking among MSMEs. Our intervention is motivated by low adoption rates of Open Finance – a financial data sharing initiative that incorporates a broader spectrum of financial services, including insurance and pension funds – in Brazil, despite the high diffusion of digital payment systems

[17] As discussed in our Pre-Analysis Plan, we plan to study additional impacts of Open Finance adoption on downstream outcomes including credit volumes and lines of credit.

(namely, Pix) in the country and the myriad benefits of Open Finance in terms of financial inclusion. Our experiment included a sample of 1,151 microentrepreneurs who, at the onset of the study, had very little knowledge of Open Finance and displayed very low adoption rates. We show that providing targeted information on the benefits of Open Finance through a video can move the needle of adoption by more than 40%. We find that adoption is more pronounced for younger and more educated micro-entrepreneur, as well as for respondents who report stronger concerns about their personal data privacy. Consistent with a sophistication channel, treatment effects are also larger among owners with two or more business accounts. We also look at the type of financial providers adopters choose to share data with, and how individual characteristics affect these choices. We find that microentrepreneurs in the treatment group who at the onset of the intervention placed high value in having control of their data are, at follow up, more likely to share data with both their main bank and other banks compared with those in the control group. These individuals are also likely to share data with digital banks. At the same time, respondents limit data sharing to banks with which they have fewer transactions.

In future analyses, we will leverage additional administrative data from BCB to study whether microentrepreneurs assigned to the treatment group perform significantly more digital payments from their business account and access to better credit conditions.

From a policy perspective, we show that the implementation of a very simple and cost-effective intervention like a video can significantly increase the adoption of open banking initiatives. However, our results that information about Open Finance helps technology savvy (young and more educated) individuals and people with privacy concerns to overcome adoption barriers suggest that the diffusion of innovations like Open Finance may exacerbate inequalities.

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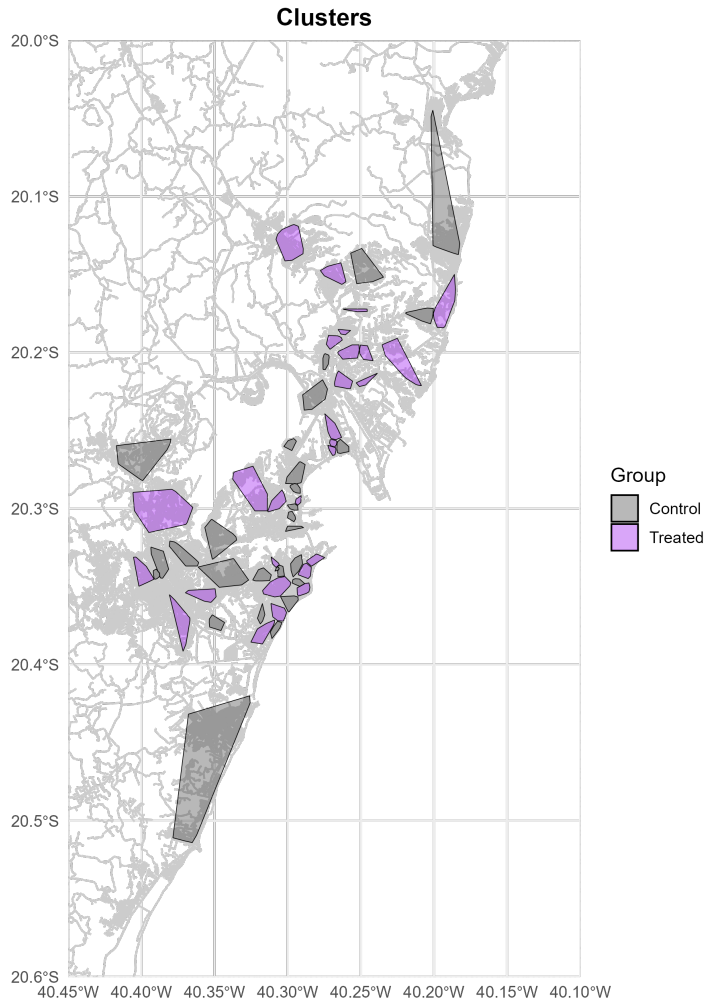
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Figures

Figure 1: Cluster Map



Notes. The figure depicts the geographical distribution of the 56 clusters, categorized into treated (purple) and control (gray) groups. Each polygon represents a distinct cluster area within the study region.

Tables

Table 1: Balance

	(1) Control	(2) Treatment	(3) (1) vs. (2)	(4) p-value from joint orthogonality test
Age < 35	0.359	0.353	0.006	0.843
Age 50 or older	0.232	0.215	0.017	0.613
Uses digital bank for receiving payments	0.668	0.749	-0.081	0.094
Incomplete primary education	0.071	0.057	0.014	0.315
Completed primary education or above	0.929	0.943	-0.014	0.315
Completed higher education or above	0.193	0.189	0.005	0.897
Completed secondary education or above	0.815	0.794	0.020	0.411
Brown / Mixed race	0.536	0.517	0.019	0.553
White	0.251	0.245	0.006	0.843
Accounting biweekly	0.303	0.321	-0.018	0.553
Accounting monthly	0.707	0.757	-0.050	0.108
Female owner	0.493	0.526	-0.034	0.377
Has internet access	0.937	0.932	0.005	0.784
Keeps separate business/personal accounts	0.673	0.677	-0.004	0.913
Requested loan (last 6 months)	0.143	0.151	-0.008	0.711
Loan approved (last 6 months)	0.124	0.130	-0.006	0.751
Solo entrepreneur (0 employees)	0.403	0.364	0.038	0.374
High revenue (10,000)	0.552	0.582	-0.030	0.531
Does knows what Open Finance is	0.098	0.111	-0.013	0.491
Uses Pix frequently	0.726	0.709	0.017	0.611
Personal data control: important.	0.907	0.909	-0.003	0.854
Personal data control: not important/neutral.	0.093	0.091	0.003	0.854
Has full personal data control	0.320	0.279	0.041	0.192
Low trust in banking	0.415	0.438	-0.022	0.404
High risk tolerance	0.295	0.300	-0.005	0.838
Not willing to take risk	0.285	0.287	-0.002	0.941
Believes taxes return as benefits	0.272	0.291	-0.018	0.486
Manages Inventory Digitally	0.246	0.264	-0.018	0.583
Receives order online	0.865	0.857	0.008	0.717
Places order online	0.786	0.802	-0.016	0.445
Willing to at least some information	0.636	0.640	-0.004	0.909
Willing to share transactional information	0.110	0.125	-0.015	0.425
Employees (continuous)	1.359	1.447	-0.088	0.619
Adhered to Open Finance	0.076	0.068	0.008	0.597
Formal Firms	0.712	0.689	0.023	0.492
How many business accounts (CNPJ) do you have?	1.373	1.306	0.066	0.418
How many personal accounts (CPF) do you use for business?	2.755	2.766	-0.011	0.920
Number of total bank accounts	4.129	4.072	0.057	0.653
N	621	530	1151	

Table 2: Open Finance Adoption

Main regression: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	0.064*	0.071**	0.071**	0.072**	0.082**
	(0.036)	(0.033)	(0.033)	(0.034)	(0.033)
Mean of OF Adoption (control group)	0.170	0.170	0.170	0.170	0.170
SD of OF Adoption (control group)	0.376	0.376	0.376	0.376	0.376
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
RI p-value (Treat)	0.071	0.033	0.033	0.040	0.025
Observations	401	401	401	401	401
R^2	0.006	0.295	0.295	0.299	0.317

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Open Finance Adoption: Education

Heterogeneity by Completed primary education or above: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	-0.077	-0.077	-0.077	-0.115	-0.087
	(0.070)	(0.070)	(0.070)	(0.091)	(0.086)
Completed primary education or above	0.098	0.025	0.025	0.002	0.030
	(0.075)	(0.069)	(0.069)	(0.079)	(0.079)
Treated × Completed primary education or above	0.140*	0.150**	0.150**	0.185**	0.164*
	(0.080)	(0.074)	(0.074)	(0.088)	(0.084)
Mean of Completed primary education or above (control group)	0.943	0.943	0.943	0.943	0.943
SD of Completed primary education or above (control group)	0.231	0.231	0.231	0.231	0.231
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.102	0.034	0.034	0.047	0.022
RI p-value (Treat + Treat × Het)	0.092	0.035	0.035	0.053	0.037
Observations	401	401	401	401	401
R^2	0.011	0.296	0.296	0.305	0.324

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Open Finance Adoption: Age

Heterogeneity by Age < 35: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	-0.022	0.015	0.015	0.009	0.016
	(0.042)	(0.040)	(0.040)	(0.042)	(0.041)
Age < 35	-0.020	-0.026	-0.026	-0.038	-0.047
	(0.052)	(0.039)	(0.039)	(0.041)	(0.038)
Treated × Age < 35	0.218***	0.144**	0.144**	0.154**	0.159**
	(0.077)	(0.067)	(0.067)	(0.069)	(0.068)
Mean of Age < 35 (control group)	0.361	0.361	0.361	0.361	0.361
SD of Age < 35 (control group)	0.481	0.481	0.481	0.481	0.481
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.003	0.005	0.005	0.004	0.001
RI p-value (Treat + Treat × Het)	0.004	0.006	0.006	0.006	0.004
Observations	401	401	401	401	401
R^2	0.032	0.304	0.304	0.313	0.332

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level. Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Open Finance Adoption: Business Accounts Usage

Heterogeneity by 2+ Business Accounts: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	0.029	0.022	0.022	0.026	0.030
	(0.044)	(0.044)	(0.044)	(0.046)	(0.046)
2+ Business Accounts	0.091**	0.008	0.008	0.009	0.005
	(0.039)	(0.035)	(0.035)	(0.033)	(0.034)
Treated × 2+ Business Accounts	0.100	0.123*	0.123*	0.117*	0.113*
	(0.076)	(0.067)	(0.067)	(0.065)	(0.067)
Mean of 2+ Business Accounts (control group)	0.457	0.457	0.457	0.457	0.457
SD of 2+ Business Accounts (control group)	0.499	0.499	0.499	0.499	0.499
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.036	0.004	0.004	0.003	0.004
RI p-value (Treat + Treat × Het)	0.024	0.001	0.001	0.002	0.002
Observations	401	401	401	401	401
R^2	0.038	0.306	0.306	0.309	0.331

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat × Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at the *cluster* level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Open Finance Adoption: Pix Business Usage

Heterogeneity by Pix Business Usage not Daily: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	0.140**	0.135**	0.135**	0.132**	0.143**
	(0.062)	(0.053)	(0.053)	(0.056)	(0.055)
Pix Business Usage not Daily	-0.016	0.006	0.006	0.008	0.012
	(0.047)	(0.029)	(0.029)	(0.030)	(0.029)
Treated × Pix Business Usage not Daily	-0.106	-0.090	-0.090	-0.093	-0.097
	(0.082)	(0.067)	(0.067)	(0.069)	(0.067)
Mean of Pix Business Usage not Daily (control group)	0.580	0.580	0.580	0.580	0.580
SD of Pix Business Usage not Daily (control group)	0.495	0.495	0.495	0.495	0.495
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.486	0.273	0.273	0.356	0.248
RI p-value (Treat + Treat × Het)	0.500	0.400	0.400	0.400	0.400
Observations	391	391	391	391	391
R^2	0.020	0.303	0.303	0.310	0.326

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Open Finance Adoption: Privacy Concerns

Heterogeneity by Personal data control: very important: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	-0.071	-0.074	-0.074	-0.078	-0.044
	(0.089)	(0.066)	(0.066)	(0.065)	(0.065)
Personal data control: very important	-0.034	-0.066	-0.066	-0.066	-0.054
	(0.060)	(0.043)	(0.043)	(0.045)	(0.045)
Treated × Personal data control: very important	0.168	0.182**	0.182**	0.182**	0.150**
	(0.101)	(0.070)	(0.070)	(0.071)	(0.073)
Mean of Personal data control: very important (control group)	0.778	0.778	0.778	0.778	0.778
SD of Personal data control: very important (control group)	0.416	0.416	0.416	0.416	0.416
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.020	0.002	0.002	0.005	0.004
RI p-value (Treat + Treat × Het)	0.016	0.001	0.001	0.006	0.008
Observations	401	401	401	401	401
R^2	0.014	0.303	0.303	0.312	0.327

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Open Finance Adoption: Trust in the Banking Sector

Heterogeneity by Low trust in banking: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	0.077	0.098**	0.098**	0.093*	0.094*
	(0.053)	(0.044)	(0.044)	(0.047)	(0.049)
Low trust in banking	-0.061	0.005	0.005	0.008	-0.005
	(0.048)	(0.036)	(0.036)	(0.037)	(0.039)
Treated × Low trust in banking	-0.029	-0.068	-0.068	-0.063	-0.041
	(0.085)	(0.068)	(0.068)	(0.070)	(0.071)
Mean of Low trust in banking (control group)	0.365	0.365	0.365	0.365	0.365
SD of Low trust in banking (control group)	0.483	0.483	0.483	0.483	0.483
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.390	0.543	0.543	0.540	0.253
RI p-value (Treat + Treat × Het)	0.403	0.560	0.560	0.588	0.302
Observations	401	401	401	401	401
R^2	0.015	0.297	0.297	0.305	0.323

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Open Finance Adoption: Risk Tolerance

Heterogeneity by High risk tolerance: OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Treated	0.053	0.079**	0.079**	0.075**	0.089**
	(0.040)	(0.035)	(0.035)	(0.036)	(0.034)
High risk tolerance	0.021	0.004	0.004	-0.002	0.003
	(0.059)	(0.046)	(0.046)	(0.046)	(0.043)
Treated × High risk tolerance	0.037	-0.027	-0.027	-0.024	-0.041
	(0.088)	(0.068)	(0.068)	(0.068)	(0.069)
Mean of High risk tolerance (control group)	0.283	0.283	0.283	0.283	0.283
SD of High risk tolerance (control group)	0.451	0.451	0.451	0.451	0.451
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.257	0.411	0.411	0.439	0.467
RI p-value (Treat + Treat × Het)	0.272	0.414	0.414	0.447	0.468
Observations	401	401	401	401	401
R^2	0.009	0.295	0.295	0.304	0.323

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Adopts Open Finance in Main and Non-Main Banks

Main regression: Main and Non-Main Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Main Bank OF Adoption					
Treated	0.071*	0.077**	0.077**	0.062**	0.055*
	(0.036)	(0.032)	(0.032)	(0.030)	(0.032)
Mean of Main Bank OF Adoption (control group)	0.122	0.122	0.122	0.122	0.122
SD of Main Bank OF Adoption (control group)	0.328	0.328	0.328	0.328	0.328
RI p-value (Treat)	0.058	0.023	0.023	0.059	0.126
Observations	401	401	401	401	401
R^2	0.010	0.270	0.270	0.279	0.294
Panel B: Non-Main Bank OF Adoption					
Treated	0.034	0.037	0.037	0.031	0.027
	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)
Mean of Non-Main Bank OF Adoption (control group)	0.048	0.048	0.048	0.048	0.048
SD of Non-Main Bank OF Adoption (control group)	0.214	0.214	0.214	0.214	0.214
RI p-value (Treat)	0.125	0.093	0.093	0.201	0.294
Observations	401	401	401	401	401
R^2	0.005	0.134	0.134	0.138	0.151
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Adopts Open Finance in Traditional (Non-Digital) and Digital Banks

Main regression: Digital and Non-Digital Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Digital Bank OF Adoption					
Treated	0.052	0.058*	0.058*	0.052	0.063*
	(0.034)	(0.032)	(0.032)	(0.032)	(0.032)
Mean of Digital Bank OF Adoption (control group)	0.135	0.135	0.135	0.135	0.135
SD of Digital Bank OF Adoption (control group)	0.342	0.342	0.342	0.342	0.342
RI p-value (Treat)	0.113	0.069	0.069	0.126	0.060
Observations	401	401	401	401	401
R^2	0.005	0.230	0.230	0.234	0.251
Panel B: Non-Digital Bank OF Adoption					
Treated	0.048	0.053*	0.053*	0.060**	0.071**
	(0.033)	(0.029)	(0.029)	(0.030)	(0.027)
Mean of Non-Digital Bank OF Adoption (control group)	0.104	0.104	0.104	0.104	0.104
SD of Non-Digital Bank OF Adoption (control group)	0.306	0.306	0.306	0.306	0.306
RI p-value (Treat)	0.153	0.094	0.094	0.060	0.020
Observations	401	401	401	401	401
R^2	0.005	0.204	0.204	0.212	0.237
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Adopts Open Finance: Privacy Concerns

Heterogeneity by Personal data control: very important: Main vs Non-Main Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Main Bank OF Adoption					
Treated	-0.063	-0.066	-0.066	-0.080	-0.070
	(0.084)	(0.068)	(0.068)	(0.066)	(0.069)
Personal data control: very important	-0.045	-0.072*	-0.072*	-0.066	-0.053
	(0.060)	(0.040)	(0.040)	(0.043)	(0.042)
Treated × Personal data control: very important	0.167	0.179**	0.179**	0.174**	0.149*
	(0.100)	(0.075)	(0.075)	(0.074)	(0.075)
Mean of Personal data control: very important (control group)	0.778	0.778	0.778	0.778	0.778
SD of Personal data control: very important (control group)	0.416	0.416	0.416	0.416	0.416
Treat + Treat × Heterogeneity = 0 p-val	0.019	0.002	0.002	0.006	0.025
RI p-value (Treat + Treat × Het)	0.019	0.003	0.003	0.007	0.030
Observations	401	401	401	401	401
R^2	0.019	0.280	0.280	0.292	0.305
Panel B: Non-Main Bank OF Adoption					
Treated	-0.059*	-0.060**	-0.056*	-0.063**	-0.058**
	(0.031)	(0.028)	(0.028)	(0.030)	(0.029)
Personal data control: very important	-0.014	-0.027	-0.021	-0.018	-0.018
	(0.030)	(0.026)	(0.025)	(0.024)	(0.025)
Treated × Personal data control: very important	0.115***	0.120***	0.114***	0.115***	0.105***
	(0.036)	(0.038)	(0.038)	(0.037)	(0.037)
Mean of Personal data control: very important (control group)	0.778	0.778	0.778	0.778	0.778
SD of Personal data control: very important (control group)	0.416	0.416	0.416	0.416	0.416
Treat + Treat × Heterogeneity = 0 p-val	0.028	0.023	0.028	0.036	0.082
RI p-value (Treat + Treat × Het)	0.022	0.018	0.022	0.052	0.093
Observations	401	401	401	401	401
R^2	0.016	0.145	0.150	0.155	0.160
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat* + *Treat* × *Heterogeneity* = *0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Adopts Open Finance: Trust in the Banking Sector

Heterogeneity by Low trust in banking: Main vs Non-Main Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Main Bank OF Adoption					
Treated	0.077	0.095**	0.095**	0.074*	0.063
	(0.049)	(0.042)	(0.042)	(0.041)	(0.045)
Low trust in banking	-0.061	-0.004	-0.004	0.004	-0.005
	(0.047)	(0.036)	(0.036)	(0.035)	(0.035)
Treated × Low trust in banking	-0.011	-0.044	-0.044	-0.038	-0.031
	(0.079)	(0.061)	(0.061)	(0.060)	(0.061)
Mean of Low trust in banking (control group)	0.365	0.365	0.365	0.365	0.365
SD of Low trust in banking (control group)	0.483	0.483	0.483	0.483	0.483
Treat + Treat × Heterogeneity = 0 p-val	0.242	0.281	0.281	0.413	0.461
RI p-value (Treat + Treat × Het)	0.250	0.309	0.309	0.435	0.499
Observations	401	401	401	401	401
R^2	0.017	0.272	0.272	0.284	0.300
Panel B: Non-Main Bank OF Adoption					
Treated	0.065*	0.073**	0.073**	0.067**	0.060*
	(0.033)	(0.033)	(0.033)	(0.031)	(0.034)
Low trust in banking	0.018	0.046	0.046	0.045	0.042
	(0.036)	(0.031)	(0.031)	(0.031)	(0.031)
Treated × Low trust in banking	-0.079	-0.095**	-0.095**	-0.094*	-0.088*
	(0.054)	(0.047)	(0.047)	(0.048)	(0.049)
Mean of Low trust in banking (control group)	0.365	0.365	0.365	0.365	0.365
SD of Low trust in banking (control group)	0.483	0.483	0.483	0.483	0.483
Treat + Treat × Heterogeneity = 0 p-val	0.694	0.491	0.491	0.441	0.420
RI p-value (Treat + Treat × Het)	0.736	0.557	0.557	0.507	0.487
Observations	401	401	401	401	401
R^2	0.012	0.143	0.143	0.152	0.159
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat × Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Adopts Open Finance: Risk Tolerance

Heterogeneity by High risk tolerance: Main vs Non-Main Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Main Bank OF Adoption					
Treated	0.052	0.074**	0.074**	0.055*	0.049
	(0.041)	(0.035)	(0.035)	(0.032)	(0.033)
High risk tolerance	0.023	0.009	0.009	0.005	0.012
	(0.050)	(0.039)	(0.039)	(0.040)	(0.039)
Treated × High risk tolerance	0.065	0.011	0.011	0.009	0.003
	(0.081)	(0.061)	(0.061)	(0.062)	(0.062)
Mean of High risk tolerance (control group)	0.283	0.283	0.283	0.283	0.283
SD of High risk tolerance (control group)	0.451	0.451	0.451	0.451	0.451
Treat + Treat × Heterogeneity = 0 p-val	0.108	0.142	0.142	0.270	0.401
RI p-value (Treat + Treat × Het)	0.118	0.163	0.163	0.287	0.406
Observations	401	401	401	401	401
R^2	0.016	0.270	0.270	0.283	0.299
Panel B: Non-Main Bank OF Adoption					
Treated	-0.005	0.006	0.006	0.000	-0.002
	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)
High risk tolerance	-0.024	-0.031	-0.032	-0.032	-0.022
	(0.027)	(0.026)	(0.026)	(0.028)	(0.028)
Treated × High risk tolerance	0.131**	0.105*	0.103*	0.103*	0.098
	(0.059)	(0.056)	(0.056)	(0.058)	(0.059)
Mean of High risk tolerance (control group)	0.283	0.283	0.283	0.283	0.283
SD of High risk tolerance (control group)	0.451	0.451	0.451	0.451	0.451
Treat + Treat × Heterogeneity = 0 p-val	0.012	0.019	0.021	0.033	0.061
RI p-value (Treat + Treat × Het)	0.005	0.008	0.011	0.020	0.038
Observations	401	401	401	401	401
R^2	0.023	0.145	0.150	0.153	0.161
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Adopts Open Finance in Digital and Traditional Banks: Privacy Concerns

Heterogeneity by Personal data control: very important: Digital vs Non-Digital Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Digital Bank OF Adoption					
Treated	-0.094	-0.097*	-0.097*	-0.101*	-0.076
	(0.065)	(0.054)	(0.054)	(0.052)	(0.052)
Personal data control: very important	-0.028	-0.054	-0.054	-0.054	-0.038
	(0.056)	(0.038)	(0.038)	(0.039)	(0.038)
Treated × Personal data control: very important	0.182**	0.193***	0.193***	0.191***	0.165***
	(0.079)	(0.060)	(0.060)	(0.060)	(0.060)
Mean of Personal data control: very important (control group)	0.778	0.778	0.778	0.778	0.778
SD of Personal data control: very important (control group)	0.416	0.416	0.416	0.416	0.416
Treat + Treat × Heterogeneity = 0 p-val	0.035	0.010	0.010	0.014	0.015
RI p-value (Treat + Treat × Het)	0.027	0.007	0.007	0.013	0.012
Observations	401	401	401	401	401
R^2	0.017	0.242	0.242	0.245	0.264
Panel B: Non-Digital Bank OF Adoption					
Treated	-0.024	-0.026	-0.026	-0.021	0.003
	(0.068)	(0.054)	(0.054)	(0.053)	(0.049)
Personal data control: very important	-0.017	-0.039	-0.039	-0.043	-0.041
	(0.045)	(0.036)	(0.036)	(0.036)	(0.036)
Treated × Personal data control: very important	0.089	0.098*	0.098*	0.103*	0.085
	(0.073)	(0.056)	(0.056)	(0.057)	(0.056)
Mean of Personal data control: very important (control group)	0.778	0.778	0.778	0.778	0.778
SD of Personal data control: very important (control group)	0.416	0.416	0.416	0.416	0.416
Treat + Treat × Heterogeneity = 0 p-val	0.069	0.020	0.020	0.012	0.005
RI p-value (Treat + Treat × Het)	0.067	0.019	0.019	0.019	0.007
Observations	401	401	401	401	401
R^2	0.008	0.208	0.208	0.216	0.239
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat* + *Treat* × *Heterogeneity* = *0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Adopts Open Finance in Digital and Traditional Banks: Trust in the Banking Sector

Heterogeneity by Low trust in banking: Digital vs Non-Digital Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Digital Bank OF Adoption					
Treated	0.075	0.091**	0.091**	0.085**	0.082*
	(0.048)	(0.041)	(0.041)	(0.041)	(0.042)
Low trust in banking	-0.006	0.048	0.048	0.053	0.038
	(0.043)	(0.034)	(0.034)	(0.034)	(0.034)
Treated × Low trust in banking	-0.056	-0.088	-0.088	-0.086	-0.064
	(0.073)	(0.060)	(0.060)	(0.060)	(0.059)
Mean of Low trust in banking (control group)	0.365	0.365	0.365	0.365	0.365
SD of Low trust in banking (control group)	0.483	0.483	0.483	0.483	0.483
Treat + Treat × Heterogeneity = 0 p-val	0.716	0.943	0.943	0.972	0.699
RI p-value (Treat + Treat × Het)	0.733	0.947	0.947	0.974	0.706
Observations	401	401	401	401	401
R^2	0.008	0.234	0.234	0.238	0.257
Panel B: Non-Digital Bank OF Adoption					
Treated	0.037	0.052	0.052	0.059	0.061
	(0.043)	(0.036)	(0.036)	(0.038)	(0.038)
Low trust in banking	-0.033	0.013	0.013	0.011	0.000
	(0.040)	(0.031)	(0.031)	(0.030)	(0.033)
Treated × Low trust in banking	0.029	0.002	0.002	0.001	0.024
	(0.069)	(0.056)	(0.056)	(0.058)	(0.061)
Mean of Low trust in banking (control group)	0.365	0.365	0.365	0.365	0.365
SD of Low trust in banking (control group)	0.483	0.483	0.483	0.483	0.483
Treat + Treat × Heterogeneity = 0 p-val	0.216	0.249	0.249	0.202	0.058
RI p-value (Treat + Treat × Het)	0.231	0.269	0.269	0.226	0.070
Observations	401	401	401	401	401
R^2	0.006	0.205	0.205	0.212	0.237
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat × Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Adopts Open Finance in Digital and Traditional Banks: Risk Tolerance

Heterogeneity by High risk tolerance: Digital vs Non-Digital Bank OF Adoption					
	(1)	(2)	(3)	(4)	(5)
Panel A: Digital Bank OF Adoption					
Treated	0.017	0.038	0.038	0.028	0.040
	(0.042)	(0.039)	(0.039)	(0.038)	(0.037)
High risk tolerance	0.005	-0.009	-0.009	-0.009	-0.004
	(0.054)	(0.047)	(0.047)	(0.048)	(0.045)
Treated × High risk tolerance	0.119	0.069	0.069	0.068	0.059
	(0.085)	(0.069)	(0.069)	(0.070)	(0.069)
Mean of High risk tolerance (control group)	0.283	0.283	0.283	0.283	0.283
SD of High risk tolerance (control group)	0.451	0.451	0.451	0.451	0.451
Treat + Treat × Heterogeneity = 0 p-val	0.054	0.068	0.068	0.112	0.101
RI p-value (Treat + Treat × Het)	0.042	0.070	0.070	0.105	0.096
Observations	401	401	401	401	401
R^2	0.016	0.233	0.233	0.240	0.257
Panel B: Non-Digital Bank OF Adoption					
Treated	0.048	0.067**	0.067**	0.073**	0.088***
	(0.035)	(0.032)	(0.032)	(0.032)	(0.030)
High risk tolerance	0.069	0.057	0.057	0.053	0.055
	(0.055)	(0.045)	(0.045)	(0.044)	(0.043)
Treated × High risk tolerance	-0.006	-0.050	-0.050	-0.045	-0.062
	(0.083)	(0.073)	(0.073)	(0.071)	(0.072)
Mean of High risk tolerance (control group)	0.283	0.283	0.283	0.283	0.283
SD of High risk tolerance (control group)	0.451	0.451	0.451	0.451	0.451
Treat + Treat × Heterogeneity = 0 p-val	0.580	0.799	0.799	0.669	0.681
RI p-value (Treat + Treat × Het)	0.599	0.822	0.822	0.679	0.686
Observations	401	401	401	401	401
R^2	0.013	0.208	0.208	0.215	0.240
Baseline OF		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. The table reports coefficients from the heterogeneity specification: *Treated*, the baseline covariate, and the interaction *Treated* × *baseline covariate*. We report the p-value from the joint significance test (*Treat + Treat* × *Heterogeneity = 0*) as well as from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

Specifications: (1) No covariates; (2) Baseline OF; (3) Baseline OF + PDS LASSO; (4) Baseline OF + PDS LASSO + City & Sector fixed effects; (5) Baseline OF + PDS LASSO + follow-up and baseline month fixed effects.

PDS LASSO indicates that high-dimensional controls were selected via `pdslasso`.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 BCB Data

7.1 Balance

Table 18: BCB Balance

	(1) Control	(2) Treatment	(3) (1) vs. (2)	(4) p-value from joint orthogonality test of treatment arms	(5) N from orthogonality test
Revenues	21252.548	22103.798	-851.250	0.776	1128
	(1963.085)	(2274.964)	(2978.737)		
Pix revenues - values	17057.977	18068.271	-1010.295	0.633	1128
	(1283.764)	(1687.160)	(2101.609)		
Revenues from Debit Card - Value	2163.456	2046.196	117.260	0.845	1128
	(397.855)	(452.443)	(597.252)		
Revenues from Credit Card - Value	2004.145	1986.778	17.368	0.985	1128
	(605.845)	(663.133)	(890.409)		
Pix revenues - quantity	139.593	146.565	-6.972	0.750	1128
	(14.109)	(16.869)	(21.800)		
Number of Pix transactions in business accounts	72.507	57.490	15.017	0.280	1128
	(11.774)	(7.336)	(13.752)		
Credit Flag	0.456	0.443	0.014	0.554	1128
	(0.017)	(0.015)	(0.023)		
Number of Credit Operations	2.192	2.038	0.154	0.362	1128
	(0.109)	(0.129)	(0.168)		
Total Credit - Value	3086.558	2475.937	610.620	0.451	1128
	(713.300)	(386.073)	(804.029)		
Share of Pix Revenues in Business Account	0.242	0.256	-0.014	0.458	1128
	(0.012)	(0.014)	(0.019)		
Formal	0.722	0.693	0.029	0.382	1128
	(0.021)	(0.025)	(0.033)		
N	607	521	1128		

Table 19: Treatment Effect on Number of Pix Transactions in Business Account

	Treatment Effect				
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
Treated	0.060	0.315**	0.315**	0.257**	0.243**
	(0.190)	(0.131)	(0.131)	(0.121)	(0.116)
Mean of the dependent variable	109.165	109.165	109.165	109.165	109.165
SD of the dependent variable	255.378	255.378	255.378	255.378	255.378
Observations	798	798	798	798	798
Pseudo R^2	0.000	0.397	0.397	0.419	0.424
Panel B: Trimmed at 99^{th} Percentile					
Treated	0.045	0.233**	0.216*	0.189*	0.168
	(0.163)	(0.115)	(0.116)	(0.106)	(0.105)
Mean of the dependent variable	91.748	91.748	91.748	91.748	91.748
SD of the dependent variable	176.185	176.185	176.185	176.185	176.185
Observations	791	791	791	791	791
Pseudo R^2	0.000	0.318	0.321	0.327	0.333
Panel C: Trimmed at 98^{th} Percentile					
Treated	0.040	0.168	0.145	0.127	0.097
	(0.134)	(0.123)	(0.123)	(0.121)	(0.120)
Mean of the dependent variable	81.431	81.431	81.431	81.431	81.431
SD of the dependent variable	140.072	140.072	140.072	140.072	140.072
Observations	783	783	783	783	783
Pseudo R^2	0.000	0.237	0.240	0.248	0.255
Controls					
ANCOVA (Transactions in Aug 2024)		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. We report the p-values from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level.

ANCOVA includes the baseline value of the outcome. Controls include City, Sector, Baseline Interview Month Fixed Effect, and high-dimentional controls selected via pdslasso

PDS LASSO selected controls: (3) , 6.bl_v14, n_pix_firm (4) none (5) , 6.bl_v14, n_pix_firm, city_1, city_2, city_3, sector_1, bl_month_1, bl_month_2, bl_month_3

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided, clustered).

Table 20: Treatment Effect on Average Pix Value in Business Accounts

	Treatment Effect				
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
Treated	0.589***	0.713***	0.710***	0.747***	0.732***
	(0.221)	(0.240)	(0.234)	(0.256)	(0.227)
Mean of the dependent variable	167.712	167.712	167.712	167.712	167.712
SD of the dependent variable	335.609	335.609	335.609	335.609	335.609
Observations	798	798	798	798	798
Pseudo R^2	0.031	0.215	0.244	0.227	0.258
Panel B: Trimmed at 99^{th} Percentile					
Treated	0.209	0.232	0.236*	0.218	0.241*
	(0.148)	(0.148)	(0.141)	(0.150)	(0.138)
Mean of the dependent variable	158.798	158.798	158.798	158.798	158.798
SD of the dependent variable	279.444	279.444	279.444	279.444	279.444
Observations	791	791	791	791	791
Pseudo R^2	0.006	0.026	0.052	0.033	0.062
Panel C: Trimmed at 98^{th} Percentile					
Treated	0.200	0.224*	0.224*	0.209	0.220
	(0.133)	(0.131)	(0.131)	(0.133)	(0.135)
Mean of the dependent variable	143.062	143.062	143.062	143.062	143.062
SD of the dependent variable	226.488	226.488	226.488	226.488	226.488
Observations	783	783	783	783	783
Pseudo R^2	0.005	0.027	0.027	0.033	0.036
Controls					
ANCOVA (Transactions in Aug 2024)		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (FUP & BL)					✓

Notes. We report the p-values from Randomization Inference (with 1,000 cluster-preserving permutations). Standard errors are clustered at geographical cluster level. ANCOVA includes the baseline value of the outcome. Controls include City, Sector, Baseline Interview Month Fixed Effect, and high-dimensional controls selected via pdslasso.

PDS LASSO selected controls: (3) , avg_pix_firm (4) none (5) , 6.bl_v14, avg_pix_firm, city_1, city_2, city_3, sector_1, bl_month_1, bl_month_2, bl_month_3

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided, clustered).

7.2 BCB Heterogeneity

Table 21: Number of Business Accounts - Two or plus

Heterogeneity by 2+ Business accounts					
	(1)	(2)	(3)	(4)	(5)
Treated	0.027	0.021	0.021	0.024	0.031
	(0.045)	(0.045)	(0.045)	(0.047)	(0.046)
2+ Business accounts	0.097**	0.010	0.010	0.011	0.004
	(0.040)	(0.036)	(0.036)	(0.034)	(0.034)
Treated × 2+ Business accounts	0.103	0.127*	0.127*	0.121*	0.127*
	(0.078)	(0.069)	(0.069)	(0.067)	(0.070)
Mean of 2+ Business accounts	0.428	0.428	0.428	0.428	0.428
SD of 2+ Business accounts	0.495	0.495	0.495	0.495	0.495
Baseline (ANCOVA)		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (BL & FUP)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.043	0.006	0.006	0.005	0.003
RI p-value (Treat + Treat × Heterogeneity)	0.023	0.004	0.004	0.010	0.004
Observations	391	391	391	391	391
R^2	0.040	0.305	0.305	0.308	0.327

Notes. The table reports coefficientsfrom the heterogeneity specification: Treated, Covariate, and the interaction Treated × Covariate. We report the p-value from the joint significance test (Treat + Treat × Heterogeneity = 0) as well as from Randomization Inference (with 1,000 cluster-presenrving permutations). Standard errors are clustered at cluster level.

Specifications: (1) No covariates; (2) ANCOVA; (3) ANCOVA + PDS LASSO; (4) ANCOVA + PDS LASSO + City Sector fixed effects; (5) ANCOVA + PDS LASSO + City Sector fixed effects + baseline and follow-up month fixed effects. ANCOVA includes the baseline value of the outcome and a dummy for missing baseline; missing baselines are set to zero prior to including the missing indicator. PDS LASSO indicates that high-dimentional controls were selected via pdslasso

PDS LASSO selected controls: (3) - (4) - (5)

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided, clustered).

Table 22: Business Credit Positive

Heterogeneity by Business credit positive					
	(1)	(2)	(3)	(4)	(5)
Treated	0.039	0.030	0.030	0.033	0.048
	(0.040)	(0.036)	(0.036)	(0.037)	(0.035)
Business credit positive	0.118	-0.104	-0.104	-0.095	-0.067
	(0.105)	(0.069)	(0.069)	(0.070)	(0.065)
Treated × Business credit positive	0.276	0.487**	0.487**	0.476**	0.433**
	(0.216)	(0.188)	(0.188)	(0.188)	(0.192)
Mean of Business credit positive	0.085	0.085	0.085	0.085	0.085
SD of Business credit positive	0.232	0.232	0.232	0.232	0.232
Baseline (ANCOVA)		✓	✓	✓	✓
PDS LASSO Controls			✓	✓	✓
City FE				✓	✓
Sector FE				✓	✓
Month FE (BL & FUP)					✓
Treat + Treat × Heterogeneity = 0 p-val	0.139	0.006	0.006	0.007	0.013
RI p-value (Treat + Treat × Heterogeneity)	0.139	0.006	0.006	0.007	0.011
Observations	391	391	391	391	391
R^2	0.031	0.316	0.316	0.319	0.336

Notes. The table reports coefficientsfrom the heterogeneity specification: Treated, Covariate, and the interaction Treated × Covariate. We report the p-value from the joint significance test (Treat + Treat × Heterogeneity = 0) as well as from Randomization Inference (with 1,000 cluster-presenrving permutations). Standard errors are clustered at cluster level.

Specifications: (1) No covariates; (2) ANCOVA; (3) ANCOVA + PDS LASSO; (4) ANCOVA + PDS LASSO + City Sector fixed effects; (5) ANCOVA + PDS LASSO + City Sector fixed effects + baseline and follow-up month fixed effects. ANCOVA includes the baseline value of the outcome and a dummy for missing baseline; missing baselines are set to zero prior to including the missing indicator. PDS LASSO indicates that high-dimentional controls were selected via pdslasso

PDS LASSO selected controls: (3) - (4) - (5)

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided, clustered).

Appendices

Table A1: Attrition Checked

VARIABLES	(1) Model 1: Treatment only	(2) Model 2: Treat + Covariates
Treatment assignment	0.0477	0.0456
	(0.0304)	(0.0307)
Female owner, yes		-0.0189
		(0.0282)
Adhered to Open Finance, yes		-0.0568
		(0.0593)
Has a balance sheet which updates at least monthly, yes		-0.0345
		(0.0400)
Owner at least completed Middle School, yes		-0.0862**
		(0.0378)
Asked for a Loan, yes		-0.143
		(0.0903)
Was given a loan, yes		0.0623
		(0.106)
Number of workers		0.00713
		(0.00726)
Number of bank accounts linked to CPF		0.0157
		(0.0155)
Number of total bank accounts		-0.0141
		(0.0137)
Formal Firms		0.0779**
		(0.0323)
Observations	1,151	1,149
R-squared	0.002	0.015

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Attrition Check Balance

	(1) Baseline and Follow-up Data	(2) Only Baseline Survey	(3) (1) vs. (2)	(4) p-value from joint orthogonality test of treatment arms
Female owner, yes	0.483	0.509	-0.026	0.384
	(0.022)	(0.026)	(0.030)	
Owner at least completed Middle School, yes	0.787	0.840	-0.054	0.025
	(0.015)	(0.018)	(0.023)	
Excluding yourself (owner), how many employees work in the business?	1.423	1.357	0.066	0.545
	(0.089)	(0.122)	(0.108)	
How many business accounts (CNPJ) do you have?	1.322	1.380	-0.058	0.285
	(0.044)	(0.055)	(0.054)	
How many personal accounts (CPF) do you use for business?	2.752	2.776	-0.024	0.797
	(0.055)	(0.089)	(0.091)	
Number of total bank accounts	4.073	4.157	-0.084	0.447
	(0.066)	(0.105)	(0.110)	
Adhered to Open Finance, yes	0.064	0.087	-0.023	0.178
	(0.009)	(0.014)	(0.017)	
Has a balance sheet which updates at least monthly, yes	0.716	0.756	-0.040	0.266
	(0.023)	(0.024)	(0.035)	
Asked for a Loan, yes	0.131	0.177	-0.046	0.043
	(0.012)	(0.018)	(0.022)	
Was given a loan, yes	0.115	0.150	-0.035	0.117
	(0.012)	(0.017)	(0.022)	
Formal Firms	0.715	0.676	0.039	0.150
	(0.019)	(0.024)	(0.027)	
N	750	401	1151	

A Desired Sources of Financing

Table A3: Desired Sources of Financing

Specification 5 across outcomes: ANCOVA + PDS LASSO + City/Sector FE + Week FE (FUP+BL)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	BankLoan	BusinessCard	PersonalCard	SupplierCred	CreditUnion	Microcredit	NoInterest
Treatment	0.041	0.059	0.029	0.059	-0.022	0.046	-0.004
	(0.055)	(0.055)	(0.055)	(0.042)	(0.035)	(0.039)	(0.041)
Baseline (ANCOVA)	0.274***	0.396***	0.337***	0.253**	0.500***	0.391***	0.319***
	(0.067)	(0.052)	(0.068)	(0.113)	(0.104)	(0.080)	(0.053)
Mean (Control, FUP)	0.213	0.291	0.278	0.204	0.122	0.196	0.235
SD (Control, FUP)	0.410	0.455	0.449	0.404	0.328	0.398	0.425
RI p-value	0.462	0.260	0.600	0.208	0.546	0.326	0.915
Observations	401	401	401	401	391	401	401
R^2	0.139	0.192	0.205	0.125	0.238	0.186	0.255

Notes. Each column reports the coefficient on *Treatment* from the same specification(Spec5): ANCOVA controls, PDS-selected controls, City Sector fixed effects,and Week fixed effects in both follow-up and baseline. Standard errors are clustered at the *cluster* level.

ANCOVA includes the baseline value of the outcome and a dummy for missing baseline; missing baselines are set to zero prior to including the missing indicator.

indicates that high-dimensional controls were selected via `pdslasso`. is from randomization inference with 1,000 cluster-preserving permutations.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: BCB Attrition Check-1,3,and 6 Months Before Baseline Survey

	(1)	(2)	(3)
	1 month before the baseline survey	3 months before the baseline survey	6 months before the baseline survey
Treatment	0.00216	0.00323	0.00539
	(0.00488)	(0.00675)	(0.00959)
Constant	0.990***	0.985***	0.975***
	(0.00351)	(0.00485)	(0.00753)
Observations	1135	1135	1135
Attrited Firms	10	15	25

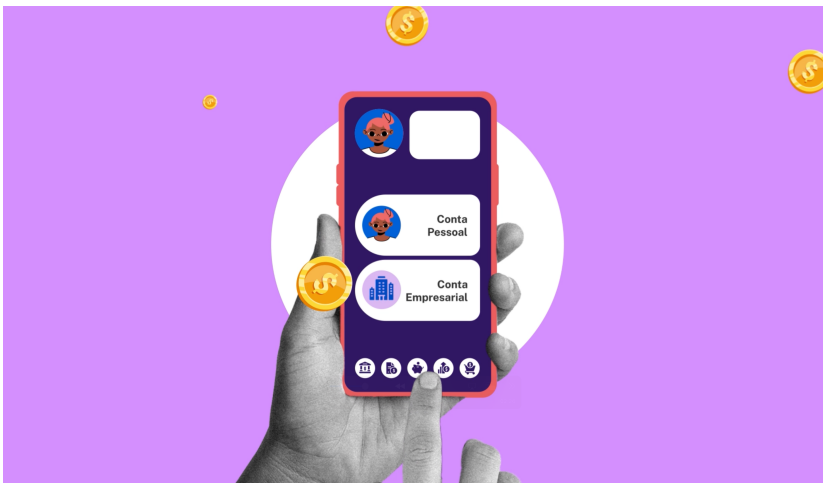
Standard errors in parentheses

Clustered stardard errors

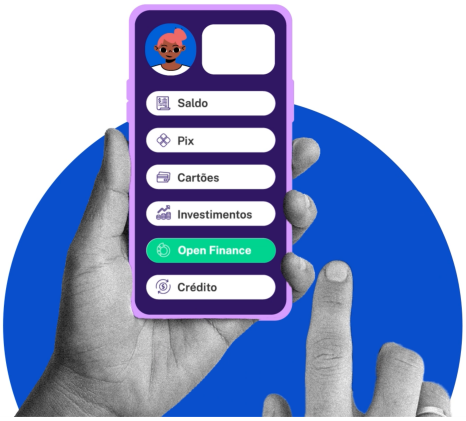
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Descriptive statistics by firm without attrition

	Mean	Median	SD	Q1	Q3	N	Zeros	Missing
Share of Pix transactions in business account	0.241	0.002	0.325	0.002	0.463	391	191	0
Share of revenues from Pix transactions over total business	0.917	1.000	0.175	1.000	1.000	391	0	0
Share of business credit in total credit	0.139	0.000	0.298	0.000	0.000	227	173	164
Indicator if business credit is positive	0.084	0.000	0.235	0.000	0.000	391	337	0
Default rate (90 + days overdue)	0.157	0.000	0.346	0.000	0.000	287	233	104
Delinquency rate (0 - 90 days overdue)	0.211	0.000	0.358	0.000	0.333	287	201	104
Total outstanding loans/ total revenues	2041.305	1.690	21306.960	1.690	10.128	287	0	104
Total outstanding loans/ number of workers	8429.326	658.420	17354.630	658.420	7811.868	391	104	0



(**a**) Control Video



(**b**) Treatment Video



(**c**) Treatment Video

Figure A1: Screenshots from Intervention Video