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FINTECH LENDING AND CASHLESS PAYMENTS

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ABSTRACT

Borrowers' use of cashless payments improves their access to capital from FinTech lenders and predicts a lower probability of default. These relationships are stronger for cashless technologies providing more precise information, and for outflows. Cashless payment usage complements other signals of borrower quality. We rationalize these empirical findings using a framework in which borrowers signal their lower likelihood of diverting cash flows through payment technology choice, and screening accuracy is further strengthened by informational complementarities. The informational synergy we uncover provides a rationale for the joint rise of cashless payments and FinTech lending, as well as for open banking.

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Banks have traditionally dominated lending, benefiting from both informational advantages and a data monopoly that have been difficult for competitors to overcome (Diamond, 1991, Rajan, 1992). Despite these barriers, the past decade has seen a dramatic rise in lending by financial technology (FinTech) companies.[1,2] At the same time, payment services have undergone rapid digitalization and disintermediation away from banks, particularly for small-value payments (Brunnermeier, James and Landau, 2019, Duffie, 2019). Compared to cash payments, cashless payments generate significantly more precise information about borrowers' income and expenses. This information is produced at low cost and can be easily used by tech-savvy lenders operating outside of traditional banking relationships, especially in the context of open banking (Parlour, Rajan, and Zhu, 2022, He, Huang, and Zhou, 2023).

Bridging these two trends, our paper provides a novel answer to the important question of how FinTech lending levels the playing field with banks, and even dominates certain lending markets (Berg, Fuster, and Puri, 2022). We document the existence of an informational synergy between cashless payments and FinTech lending and discuss its implications for the future of banking. Borrowers' use of payment technologies with varying levels of informational precision appears to significantly influence their access to capital from FinTech lenders. In the context of unsecured lending to small businesses in a developing economy, we find that greater use of cashless payments leads to improved financing outcomes: higher likelihood of loan approval, lower interest rates, and larger loan amounts from FinTech lenders. In addition, small firms that make greater use of cashless payments are less likely to default on loans from FinTech lenders, all else being equal. These effects are more pronounced for cashless outflows and payments that provide more precise information. Furthermore, the signals derived from cashless payment usage complement, rather than substitute, other indicators of borrower quality, such as credit score or expenditure volatil-

[1]The Financial Stability Board (FSB) defines FinTech as "technologically enabled financial innovation." Unlike traditional bank lending, FinTech lending typically relies on electronic technologies and alternative data sources to assess loans without the need for established relationships or deposit-taking.

[2]According to the Bank for International Settlements, the global annual volume of FinTech lending—combining new credit extended by both stand-alone FinTech firms and large technology companies—grew from \$17 billion to \$769 billion between 2013 and 2019, reflecting an annual growth rate of 87.3%. The rise of FinTech lending has been especially pronounced in developing economies (Claessens et al., 2018). In the United States, FinTech credit has seen substantial growth in key lending markets, including the mortgage market (e.g., Buchak et al., 2018, Fuster et al., 2019), and has developed significantly in the small-business lending market (e.g., Erel and Liebersohn, 2021, Gopal and Schnabl, 2022).

ity. These empirical patterns can be explained by a simple framework in which borrowers signal a lower likelihood of diverting cash flows through their choice of payment technology. This selection effect is further reinforced by an accuracy effect, whereby better-performing firms benefit more from the use of cashless payments.

Broadly, our findings provide a rationale for the joint rise of FinTech lending and cashless payments, as well as for the emergence of FinTech platforms and BigTech lending. As stand-alone payment firms and online marketplaces increasingly offer lending products, they are able to capitalize on the informational synergy between cashless payment processing and lending.[3] Furthermore, our study provides a strong economic justification for expanding access to historical payment records, as seen with open banking regulatory initiatives.

To conduct our empirical analysis, we use comprehensive loan application-level data from Indifi. One of the leading FinTech lenders in India, Indifi focuses on unsecured lending to small businesses and provides us with a data set that covers more than 300,000 applications from 2015 to 2022. This empirical laboratory is uniquely suited to tackling our research questions for several reasons. First, India has been experiencing a pronounced rise in both cashless payments and FinTech lending, following both public and private initiatives, and these developments have been attracting global attention.[4] Second, unsecured lending to small businesses in a developing economy represents a context in which information asymmetry is particularly large, which makes it a compelling setting to study the informational value of payment records. Third, our data include the entire information set that the FinTech lender observes and uses, including applicants' business characteristics, credit bureau data when available, unique applicant identifiers that allow for identifying repeat borrowers, and most importantly, detailed payment records with different levels of information precision. This feature allows us to trace how payment information of different types and with varying levels of informational precision affects loan screening and predicts financing outcomes, and to shed light on the implications of open banking. Fourth, our

[3] In the United States, PayPal, Square, and Stripe, originally stand-alone payment service providers, have all begun offering loans. Globally, Amazon and Alibaba are notable examples of marketplaces that now offer loans to their partners, a trend known as "BigTech lending" (Liu, Lu, and Xiong, 2022).

[4] India's annual volume of FinTech credit has grown from $9 bn in 2012 to $150 bn in 2020. See www.statista.com/statistics/1202533/india-digital-lending-volume and www.techwireasia.com/2021/03/indias-road-to-becoming-a-cashless-economy. At the same time, India has been a leading economy in the rollover of fast cashless payments, as documented in the studies by Dubey and Purnanandam (2023), Alok et al. (2024) and Copestake et al. (2025).

setting allows us to isolate this informational channel for screening because possible benefits of cashless payments for monitoring, collecting payments, or bundling payments with other financial products are not available in the context we study. Finally, the setting supports an identification strategy based on the effects of the 2016 Indian Demonetization on payments, which helps us rule out a spurious relationship between financing outcomes and cashless payment use and supports a causal interpretation of our findings.

We first develop a text-analysis methodology to classify each transaction from the payment records into cash and cashless payments. Within cashless payments, we can further separate between information-intensive and information-light methods of payments, depending on whether payments are partly aggregated and whether the payment counterparty is identifiable. We next construct measures of the use of cashless payments at the application level by calculating the value-weighted share of transactions executed with cashless payments, either aggregating or separating inflows and outflows.

We find that a higher use of cashless payments is associated with improved access to capital from FinTech lenders. Equipped with our comprehensive data and the measures of payment technology usage, we study how cashless payment usage of varying types and informational precision predicts financing outcomes from FinTech lending along both the extensive and intensive margins. We control nonlinearly for a comprehensive set of firm characteristics such as size, age, three-digit zip code, and business owner's credit score. Although the information revealed by cashless payments can be positive or negative, we find that applicants with a higher share of cashless payments on their record are on average significantly more likely to obtain a loan, and they receive lower interest rates and a higher loan amount conditional on their loans being approved. These results are robust to a host of alternative specifications and measures of cashless payment use, which suggests that the findings are unlikely to be driven by measurement errors or unobserved variable bias. Moreover, we find a large economic magnitude for these relationships. Controlling for other observable characteristics, including business owner credit score and applicant industry, a one-standard-deviation increase in cashless payment use is associated with an increase in the likelihood of obtaining a loan by 2 percentage points, or 10% of the baseline. Conditional on obtaining a loan, a one-standard-deviation increase in cashless payment use corresponds to a decrease in interest rate of 50 basis points (bps), and an increase in approved loan amount of 14%.

We also find that successful applicants who use more cashless payments are also significantly less likely to default, all else equal. A one-standard-deviation increase in cashless payment use corresponds to a 2 percentage point reduction in default probability, or a 13% reduction from the baseline probability. This result is robust to controlling for the general set of borrower characteristics, including business owner's credit score, as well as for the intensive-margin outcomes of loan screening such as interest rate and loan amount. This finding provides a direct rationale for FinTech lenders to screen based on cashless payment usage, and strengthens the external validity of the previous findings.

The empirical results above raise an important question: why does borrowers' use of cashless payments in itself (rather than the content) matter for lending decisions and financing outcomes, and with such large economic significance?[5] The pronounced relationship between cashless payment use and default strongly suggests that payment technology choice correlates with borrower creditworthiness. To further flesh out the economic mechanism, we conduct several additional tests uniquely enabled by our data to highlight two complementary economic effects. We then develop a simple model to articulate and unify these effects formally.

We first highlight the findings regarding cashless payments and defaults as a selection effect: less creditworthy applicants are less likely to use cashless payments because the resulting payment records may reveal their lower credit quality, or provide a benchmark that will facilitate the identification of bad behaviors detrimental to the lender. Building further on this rationale, we show that the share of cashless payments in outflows has stronger predictive power for financing outcomes and default compared to that in inflows in terms of both statistical significance and economic magnitude. This finding is consistent with the hypothesis that high usage of cashless payments and the transparency it brings reduces the possibility of conducting cash-flow-diverting activities, such as using company resources for personal spending, and in turn the likelihood of default. Moreover, we show that the predictive power of the cashless payment share on financing outcomes is more pronounced for information-intensive payment records, that is, those with verifiable counterparty informa-

[5]While it is natural to expect that obvious directional signals derived from payment records (e.g., observing fines or gambling expenses) should be predictive of creditworthiness, payment technology usage itself is a priori neutral in that regard.

tion, as opposed to information-light payment records, such as aggregated or anonymized payments. We view these results as consistent with a disciplining effect of informative payment records, which in turn might facilitate borrower sorting into technologies.

Importantly, the higher likelihood of obtaining a loan when using more cashless payments continues to hold when running a test focused on repeat applicants that includes applicant fixed effects. Such a test rules out potential alternative explanations that unobserved time-invariant firm-level characteristics may have driven both the use of cashless payments and financing outcomes. In fact, the share of cashless payments in outflows becomes even more central for repeat borrowers in predicting financing outcomes. These results illustrate that cashless payment usage is of particular interest for lenders because it provides incremental information about downside risk that is not captured by usual observable measures such as credit score, business model, industry, or any fixed characteristic.

We further find that the positive effects of using cashless payments on financing outcomes are significantly stronger for firms exhibiting other signals of high creditworthiness. We use two distinct signals: the applicant's credit score, which is easily accessible by any lender, and the volatility of payment outflows, which can be uniquely constructed from the content of payment records and proxies for risk. We highlight this complementarity as an accuracy effect in that high cashless payment usage makes other signals more informative, which allows good borrowers to earn even more favorable financing outcomes. This finding is broadly consistent with Berg et al. (2020), who find that customers' "digital footprints" complement rather than substitute for credit bureau information in predicting borrowing and default outcomes.

We conclude our empirical analysis with an instrumental variable analysis exploiting the Indian Demonetization, which supports a causal interpretation of the relationship between cashless payment usage and improved financing outcomes. We instrument applicant reliance on cashless payments with an interaction term between an indicator variable for the applicant banking at a currency chest bank branch and an indicator for the years in which cash usage was most affected.[6] We strengthen the claim for a causal relationship between cashless payments usage and the likelihood of obtaining a loan, particularly so for high-credit-score applicants. This interaction analysis further addresses concerns about

[6] A currency chest bank branch distributes new banknotes and coins. See Section 1 for more details.

unobserved variable bias, including time-varying bias, by showing that FinTech lenders specifically incorporates cashless payment usage in their screening decision. A more forceful interpretation of this result is that it provides evidence of the disciplining role of cashless payments, as their use translates into and thus signals lower downside risk. This interaction analysis also strengthens the claim for complementarity with other signals, thereby addressing concerns about bias resulting from potential correlation between cashless payment usage and credit score.

To unify our empirical findings and formalize the selection and accuracy effects, we finally develop a model that builds on Parlour, Rajan, and Zhu (2022). This model provides further insights about why lenders incorporate borrowers' use of cashless payments in their screening decision. The key intuition of the model is that cashless payment records provide a benchmark for production outcomes. This benchmark matters particularly in case of default, when the discovery of potential resource-diverting activities may lead to future legal or economic penalties to the borrower. Cashless payment records thus serve as a form of "digital collateral" because it is more costly for bad borrowers to "post" their records. Our model also connects to the idea of instrumental privacy preferences as studied in Chen et al. (2023), in that bad borrowers face a higher cost in sharing their payment records.

Our paper contributes to the literature on both FinTech lending and payment technology (see Vives (2019), Allen, Gu, and Jagtiani (2021), and Berg, Fuster, and Puri (2022) for surveys). On the lending side, several studies explore the forces behind the boom of FinTech lending in household finance (Buchak et al., 2018, Fuster et al., 2019) and small-business loans (Erel and Liebersohn, 2021, Gopal and Schnabl, 2022, Beaumont, Tang, and Vansteenbergh, 2025). Recent literature further studies lending by large technology platforms, that is, "BigTech" lending (Frost et al., 2019, Liu, Lu, and Xiong, 2022). These studies highlight regulatory arbitrage, convenience, and speed as main determinants of the development of FinTech and BigTech lending. Another related literature considers peer-to-peer or marketplace lending specifically, which relies on end-investor screening and direct investing; recent studies include Iyer et al. (2015), Tang (2019) and Vallee and Zeng (2019).[7]

[7]Despite the overall growth of FinTech lending, this peer-to-peer aspect has been losing momentum because such platforms have been increasingly catering to large, institutional investors, as Vallee and Zeng (2019) predict. We do not focus on the peer-to-peer or the marketplace aspect, but rather on the broader FinTech lending model that relies on new technologies to process information.

Our contribution to this literature is to identify a novel informational channel for FinTech lenders to level the playing field with banks by leveraging the use of borrowers' cashless payments. In this regard, our paper relates to Berg et al. (2020), Vissing-Jorgensen (2021), and Lee, Yang, and Anderson (2025), who document that simple "digital footprints" or consumer spending data predict household defaults on top of credit scores. Ouyang (2023) shows that cashless payments improve credit access for households. Complementing these studies, we focus on small businesses' payment records, which are directly generated as by-products in production and hard to manipulate. In particular, we examine how the use of cashless payments (rather than the actual information content of cashless payment records) impacts financing outcomes, and we provide a rationale for why FinTech lenders incorporate payment technology choice in their screening decisions. In this respect, our study also complements Bartlett et al. (2022) and Fuster et al. (2022), who study the extent to which new inference technologies such as machine learning can differentially affect financing outcomes of certain applicant groups.

On the payment side, existing literature mainly focuses on the direct benefits of cashless payments on consumption and production, and determinants for their adoption (e.g. Jack and Suri, 2014, Muralidharan, Niehaus, and Sukhtankar, 2016, Dubey and Purnanandam, 2023, Higgins, 2024). More relatedly, Chodorow-Reich et al. (2020) and Crouzet, Gupta, and Mezzanotti (2023) provide comprehensive studies of the 2016 Indian Demonetization on the adoption of cashless payments, focusing on testing money neutrality and network externality, respectively. We complement these studies by showing how and why borrowers' use of cashless payments affects their financing outcomes, highlighting another force towards their adoption.

Our focus on the interaction between cashless payments and FinTech lending allows us to contribute to a burgeoning literature on open banking, which highlights the synergy between payment information and lending. Closely related to our work, Parlour, Rajan, and Zhu (2022) theoretically study competition between stand-alone FinTech payment service providers and traditional banks providing both lending and payment services. They show that such competition may disrupt the information spillover within a bank, generating rich welfare implications. He, Huang, and Zhou (2023) examine the lending competition between traditional banks and FinTech lenders when borrowers share their bank data with

FinTech lenders and examine the welfare implications of open banking. Empirically, a number of contemporaneous papers study the nature and evolution of loan screening under the development of open banking (Nam, 2023, Rishabh, 2023) and its macroeconomic implications (Babina et al., 2025). More broadly, studying the synergy between cashless payments and lending allows us to connect to the large banking literature that highlights banks' information advantages (see Diamond (1991) and Rajan (1992) for pioneer work and Liberti and Petersen (2019) for a survey) and documents that a bank may learn from relationship-specific deposit flows to facilitate lending to the bank's depositors (e.g., Berlin and Mester, 1999, Mester, Nakamura, and Renault, 2007, Norden and Weber, 2010, Puri, Rocholl, and Steffen, 2017), highlighting the informational spillover between the two sides of a bank's balance sheet. Our paper complements this stream of research by showing that the existence of an integrated balance sheet or relationships inside the same bank is not a necessary condition for the informational spillover between lending and payments.

Finally, our paper connects to the literature on data sharing.[8] We add to this literature by showing that sharing borrowers' payment records leads to better financing outcomes. Our analysis also complements Farboodi and Veldkamp (2020, 2021), Cong, Xie, and Zhang (2021), and Cong et al. (2021), who examine the interaction between macroeconomic growth, adoption of information technologies, and data accumulation.

The rest of the paper is organized as follows. Section 1 reviews the Indian payment and lending landscape and the institutional background of the 2016 Demonetization. Section 2 describes our data from a leading Indian FinTech lender and our construction of cashless payment usage measures. Section 3 presents the main empirical results linking cashless payment usage to financing outcomes and default. Section 4 examines mechanisms, focusing on payment outflows, informational precision, within-firm variation, and complementarities with other quality signals. Section 5 reports our instrumental variable analysis exploiting variation from Demonetization. Section 6 develops a simple model unifying the empirical findings. Section 7 discusses the scope of our study, and Section 8 concludes.

[8]See Admati and Pfleiderer (1990) for early work and Bergemann and Bonatti (2019) for a recent survey. For example, Jones and Tonetti (2020) argue that the nonrivalry of data implies increasing returns to sharing data and better resource allocations. Bonatti and Cisternas (2020) and Ichihashi (2020) show that aggregating past purchase histories into a transferrable score or sharing consumer data in general leads to more targeted price discrimination.

1 Background

1.1 Payment and Lending Landscape in India

In recent years, India has undergone a transformation in its payment landscape. State-led initiatives and investments have fostered rapid and widespread adoption of cashless payment methods. The Unified Payments Interface (UPI), launched in 2016, allows consumers and merchants to digitally settle payments across the nationwide banking network, offering a digital payment ecosystem that is free, instantaneous, and accessible on any connected device through various channels (see Dubey and Purnanandam (2023), Alok et al. (2024) and Copestake et al. (2025) for more details). As of 2022, UPI processes over $1 trillion dollars annually, equivalent to one-third of India's GDP, and 52% of its 88.4 billion digital transactions.[9] At the same time, India is witnessing a surge in smartphone usage and affordable internet connection. Government initiatives such as Digital India prioritize improving online infrastructure across rural and urban areas alike. Two additional factors play an important role in India's shift to digital payments: the program "Pradhan Mantri JanDhan Yojna," which has created bank accounts for nearly every household in the nation, and the forced 2016 to 2018 demonetization of large-denomination banknotes, which we discuss further below.

By contrast, the lending landscape in India is characterized predominantly by traditional banking practices. State-owned banks remain the primary source of credit for most individuals and businesses across the country, providing 71% of credit as of 2015. However, these banks have been slow to adopt new practices and technologies (Mishra, Prabhala, and Rajan, 2022). Large segments of the population face challenges in accessing these traditional lending institutions and are forced to rely on collateralized lending or informal lenders (Ravi, 2019).[10]

1.2 The 2016 Indian Demonetization, and the Role of Currency Chest Banks

On November 8, 2016, the Indian government suddenly withdrew a significant portion of large-denomination banknotes from circulation. This attempt to curtail the shadow

[9] See https://www.economist.com/special-report/2023/05/15/a-digital-payments-revolution-in-india.

[10] A 2012 study from All-India Debt and Investment Survey found that reliance on informal lenders by rural households is as high as 44%.

economy created significant frictions to cash usage in the years that followed. Depositors who happened to bank at "currency chest" branches, however, enjoyed better access to new banknotes and to cash in general.

Numbering more than 3,000, these currency chest branches are bank branches selected by the Reserve Bank of India (RBI) to store and distribute Rupee banknotes and coins. A typical bank may have some regular branches and some currency chest branches. The designation of currency chest bank branches is driven mainly by the RBI striving for an even geographical distribution of branches to distribute cash efficiently to the entire population (see Aggarwal, Kulkarni, and Ritadhi, 2023 for more details).

2 Measuring Cashless Payment Usage: Data and Methodology

2.1 Data

The empirical analysis of this study relies on novel data provided by one of the largest Indian FinTech lenders, Indifi, which covers more than 300,000 unsecured loan applications from micro and small businesses from 2015 to 2022. The data set includes the entire information set gathered by the FinTech lender to screen applications, financing outcomes, and loan performance as of 2022.

Indifi is an online lending platform that grants unsecured loans to micro and small businesses, such as taxi drivers and corner stores, in India. To screen applications, Indifi collects information on loan applicants from several sources: an electronic form filled out by applicants, data from the Indian credit bureau, and for some applications information from industry partners such as online marketplaces. As shown in Figure A1 in the Internet Appendix, Indifi requires applicants to submit the last six months of bank statements from the account that will be used for receiving and repaying the loan.[11] Indifi then uses a third-party provider to parse and harmonize the applicant firms' transaction-level payment data from these bank statements. Indifi does not access payment records in that bank account after processing the application and thus is unlikely to have an advantage in monitoring the loan.[12] Indifi finances its loans through a mix of outside investors and an affiliated fund,

[11]In practice, Indifi typically obtains these outside data by asking loan applicants to link their bank deposit accounts to the Indifi loan application protocol or to directly upload bank statements in pdf forms.

[12]We note that even when the bank account is linked and the information extracted through an application programming interface (API), Indifi still only has access to the applicant's previous bank statements

but it does not rely on investor screening and thus provides investors with no loan-specific information.[13]

Our data set combines the data sources for all loan applications received by Indifi from September 2015 to November 2022. For all applications, we have information on applicant characteristics, such as industry, location, number of years of business operations, and age of the business owner. For applicants who possess a credit history, our data set also includes the associated credit bureau data, which contains among other variables the Indian credit score of the business owner, the Cibil score, the start date of their credit history, the number of previous loans, and their past loans' amounts and interest rates. We filter out all applications that do not include transaction-level payment data because Indifi automatically rejects incomplete applications. After filtering, we observe more than 152 million transactions conducted by 316,719 small firms that completed a full application. Around half of these applications are repeat applicants, which we can trace with a unique applicant identifier.

2.2 Identifying and Classifying Payment Technology

By conducting text analysis on the payment labels from the bank statements, we identify the technology used for more than three-quarters of the payments appearing on these records and construct proxies for payment technology usage. We summarize the key steps of the procedure below; we provide a more detailed elaboration in Appendix A.

We first group identifiable payment records into two broad categories: cash and cashless payments. Cash payments are cash deposits or withdrawals, either at a branch or an ATM. Cashless payments include any non-cash payments for which we can identify the payment technology. Specifically, cashless payment technologies in our data include certified checks, Internet banking transfers, mobile banking transfers, Point-of-Sale (POS) machine transactions, and transfers in third-party mobile applications. To capture the different quantity of information contained in a payment record, we further classify information-intensive payment records as those that do not aggregate transaction-level payment records and whose payment counterparty can be identified in the record.

for the six months prior to the application, but not future bank statements.

[13]This funding choice is consistent with the prediction of Vallee and Zeng (2019) that as FinTech lending matures, it converges back to a model in which loan screening is fully implemented by the intermediary.

For each applicant, we then calculate the amount-weighted share of payments conducted in cashless technology over the six months before the application, separately for both inflows and outflows, ignoring payment records whose technology cannot be identified.[14] We take the simple average of these two quantities and label this proxy the share of cashless payments, our main variable of interest. We calculate the share of information-intensive cashless payments in a similar way.

2.3 Summary Statistics

Table 1 provides summary statistics on the data we use in our empirical analysis. Panel A provides general statistics on applicants. Business owners and the businesses they manage are relatively young, with the average owner being 37 years old and their business four years old. The owners' Cibil score interquartile is 676 to 749, which corresponds to satisfactory to good credit scores.

[Insert Table 1 here]

Panel B of Table 1 provides summary statistics for the payment records and the empirical proxies for payment technology that we construct from them. The firms from our sample rely primarily on cashless payments for conducting their business, with an average share of cashless transactions of 77.9%.[15] Average cashless payment intensity is comparable across inflows and outflows. Table A1 in the Internet Appendix provides a further breakdown of the share of cashless payments by industry. These data also confirm that applicants are small to micro firms, with average monthly revenue around INR ₹1.4m (USD $17k) and monthly revenues for the bottom quartile below INR ₹147k (USD $1.7k).

Lastly, in Panel C, we present summary statistics for application outcomes, that is, whether the application is approved, if so for what amount, interest rate, maturity, and whether the loan is disbursed. Indifi accepts around 21% of complete applications in our sample and offers loans with an average amount of INR ₹535k (USD $6k), an average interest rate of 25.4%, and an average maturity of 20 months. The average loan size is about 15 times the average balance in the applicant's bank accounts, underscoring the

[14] The shares of cash and cashless payments thus add to one.

[15] The share of cash payments is likely underestimated because the applicants might receive cash from their clients, which they subsequently spend without depositing it in their bank account.

economic significance of the loans we study. We also find that as of November 2022, 18% of the matured and outstanding loans are, in default, which suggests a relatively high level of risk.

3 Cashless Payments Usage and Access to Financing

3.1 Cashless Payments and Financing Outcomes

We first document that high cashless payments usage by the applicant prior to their application is associated with significantly improved financing outcomes with the FinTech lender. We consider three main dependent variables that jointly capture the extensive and intensive margins of financing outcomes: i) an indicator variable for the loan application being approved by the lender, ii) the interest rate offered on the loan conditional on approval, and iii) the loan amount offered. We use the previously defined share of cashless payments as the main explanatory variable in cross-sectional regressions, and we interpret this variable as capturing the extent of cashless payment use by the applicant.

For illustrative purposes, Figure 1 presents binned scatter-plots of these three outcome variables against the share of cashless payments, controlling only for general time trends by including application year-month fixed effects. The figure shows a strong positive correlation between the use of cashless payments and financing outcomes. When a firm exhibits a larger share of cashless payments in the payment records it submits when applying for a loan, the lender is significantly more likely to offer a loan (Panel A), charge a lower interest rate (Panel B), and grant a larger loan (Panel C). The economic magnitudes of these unconditional relationships are large.

[Insert Figure 1 here]

To make the test more precise and reduce the possibility of unobserved variable bias, we next run formal regressions of the three financing outcomes on the standardized share of cashless payments, including a comprehensive set of granular controls and fixed effects allowing for nonlinear relationships. Table 2 provides the regression results. We use the following baseline specification:

$$FinancingOutcome_i = \beta\, CashlessShare_i + \gamma X_i + \sum_k \theta_{F_k(i)} + \varepsilon_i\,, \tag{3.1}$$

where $FinancingOutcome_i$ is an indicator for obtaining a loan, the interest rate offered, or the loan amount offered, $CashlessShare_i$ is the standardized share of cashless payments defined in Section 2.2, X_i is a set of linear controls, namely, credit history length, business age, log of owner's age, and log number of payments, and $F_k(i)$ are fixed effects for industry and application month included in all specifications to address potential composition effects along these dimensions and to control for the general information set that the lender has. In columns (2), (4), and (6), we further add fixed effects for revenue deciles to nonlinearly control for business size, three-digit zip-code fixed effects to mitigate potential geographical composition effects, and 10-point-range Cibil score fixed effects to nonlinearly control for credit score. By doing so, we further mitigate concerns that borrower characteristics potentially correlated with their use of cashless payments are driving the relationship we document. Importantly, because we observe the same information set as the lender, and because our dependent variable is a decision from that same lender, unobserved variable bias is significantly less likely in our setting than in a standard empirical banking settings. The results in all columns are statistically significant, robustly showing that a higher share of cashless payments is associated with a significantly higher likelihood of obtaining a loan, a significantly reduced interest rate, and a significantly higher loan amount.

[Insert Table 2 here]

As shown in Table 2, the relationship between cashless payments and financing outcomes remains economically significant when including a battery of controls. Specifically, the estimate regarding loan approval in column (2) with the full set of controls suggests that, all else equal, a one-standard-deviation increase in the share of cashless payments corresponds to an increase in the likelihood of loan approval of 2%, which represents 8% of the baseline likelihood of getting approved in our sample. In terms of interest rates conditional on loan approval, the estimate in column (4) suggests that a one-standard-deviation increase in cashless payments further corresponds to a decrease in interest rate of 44 bps. A one-standard-deviation increase in cashless payment use is also associated with a 13% increase in offered loan amount.

3.2 Cashless Payments and Loan Defaults

Next, when controlling for observable characteristics and conditioning on a loan being offered, we find that a high use of cashless payments is strongly predictive of a lower likelihood of default.

To this end, we first present a binned scatter-plot of the likelihood of default against the use of cashless payment in Figure 2, residualizing for application year-month fixed effects. The plot highlights a strong negative relationship between cashless payment usage and default.

[Insert Figure 2 here]

We then regress $\mathit{Default}_i$, an indicator variable for a loan having defaulted (as of November 2022) in our sample, on the standardized share of cashless payments, progressively introducing our standard set of controls. We consider the following specification (3.2):

$$\mathit{Default}_i = \beta\, \mathit{CashlessShare}_i + \gamma X_i + \sum_k \theta_{F_k(i)} + \varepsilon_i \,. \tag{3.2}$$

Columns (1) and (2) of Table 3 report the results. We find that a higher share of cashless payments is associated with a significantly lower likelihood of loan default. This relationship is economically large: a one-standard-deviation increase in the share of cashless payments reduces the probability of default by 2 percentage points, or 11% of the baseline default rate.

We further include in specification (3.2) two additional controls corresponding to the intensive margin of screening outcomes: the log of the offered interest rate, and the log of the loan amount disbursed. We report the results in columns (3) and (4) of Table 3. The coefficient on the share of cashless payments is smaller but remains significant after we control for these screening outcomes. These results imply that the lender could have incorporated even more of the information content of cashless payments in screening and pricing loans.[16]

[16]There are two main economic rationales for why the lender would not fully exploit the information content of cashless payments when setting loan prices and amounts. First, at the time of screening, the lender does not observe defaults in the same way an econometrician does ex-post; full incorporation of this information involves a learning process and is progressive. Second, the FinTech lender may have market

[Insert Table 3 here]

We also look at whether cashless payment usage predicts time to delinquency (conditional on delinquency) in columns (5) and (6), which corresponds to the intensive margin of default, and repayment speed in columns (7) and (8), which proxies for short-term liquidity needs.[17] We find that higher cashless payment usage is associated with later default, which we view as consistent with the previous result on the extensive margin of default. We also find that higher cashless payment usage is predictive of faster repayment, which is suggestive of cashless payments usage being predictive of short-term liquidity needs. This result is consistent with and complements Liu, Lu, and Xiong (2022), who show that BigTech lenders also better serve borrowers with higher short-term liquidity demand.

In the Internet Appendix, we provide a series of robustness checks on these results in Table A2 through Table A8, and we find consistent results. These robustness checks include the breakdown of different sectors, different fixed effects, clustering, and sample splits by subperiod, by credit score, and by firm size. In Table A9 we find that higher cashless payments are associated with a lower take-up rate of offered loans, which suggests that these borrowers having more outside credit optons, consistent with our main results.

3.3 Other Transaction Records

Although we focus on cashless payments due to their economic importance, we also investigate whether similar economic relationships hold for other types of transaction records. We document that our previous findings generalize to online marketplace transaction records such as those used by BigTech lending. The contrast in this context pertains to transactions executed by the firm on the online marketplace versus those executed outside the online marketplace, for example, at a brick-and-mortar location.

To this end, we take advantage of another unique feature of our data. For a subset of applicants, Indifi also has access to the applicant firms' transaction data on a set of partner online marketplaces. These data are conceptually close to cashless payment records as

power over applicants with high cashless payment usage if traditional banks are not screening on this dimension.

[17]Note that due to recently introduced regulation that applies to repayment data in India, we did not run these regressions ourselves, but rather provided the code to Infidi which ran it internally and provided us with the outputs.

both are directly generated by the economic activity of the applicant firms and provide information in digital form that can be easily used by the lender for screening purposes. We combine the average monthly amount of revenues observed from this source and the average monthly total revenues observed from payment records in the bank statements to calculate the share of revenues from online marketplaces of any given firm.

We repeat our baseline specification (3.1) using the share of firm revenues from online marketplaces as the explanatory variable, with the full set of controls as well as a control for the share of cashless payments.[18] Table 4 reports the results. We find that a higher share of online marketplace transactions is associated with a significantly higher likelihood of the loan being approved, a lower offered interest rate, a larger offered loan amount, and a lower default likelihood. These results suggest that having a larger share of economic activities on online marketplaces is associated with better financing outcomes in a similar manner as cashless payments. Moreover, the benefits related to the information provided by payment records and marketplace records appear to be cumulative, which provides a rationale for lenders to source outside data of different types.

[Insert Table 4 here]

4 Why is Cashless Payments Usage Useful for Borrower Screening?

The preceding section demonstrates that the use of cashless payments is linked to both improved financing outcomes and a reduced likelihood of default. While the lower default rate can partially explain the improved financing outcomes, it is not immediately clear why cashless payment usage would inherently signify creditworthiness. We therefore run further empirical tests to discern the mechanisms underlying these associations. We find that when applicants select their payment technology, especially during spending, or when the records possess higher informational precision, the connection between default rates and the proportion of cashless payments becomes even more marked. Moreover, when analyzing repeat applications and incorporating applicant fixed effects, our results show that an internal increase in a firm's cashless payment usage enhances the chances of securing

[18] In India, transactions on online marketplaces are not necessarily paid through cashless payments, as a significant share of transactions are paid in cash at delivery.

a loan.[19] The information derived by the lender from cashless payment usage also appears to complement other quality indicators, such as credit scores or volatility in spending. Collectively, these supplementary findings point to a mechanism whereby cashless payment usage per se correlates with an applicant's creditworthiness.

4.1 Cashless Share of Payment Inflows versus Outflows

We first study whether the effect of cashless payment usage varies across payment inflows and outflows. We re-run our baseline specification (3.1), replacing our main explanatory variable $\mathit{CashlessShare}_i$ with measures that separately consider incoming and outgoing transactions. Results are displayed in Panel A of Table 5.

[Insert Table 5 here]

This exercise reveals that cashless payment usage for inflows and that for outflows both affect financing outcomes but outflows are particularly relevant in that regard: the economic magnitudes for predicting the likelihood of being approved, loan amount, and default risk are twice as large for outflows compared to inflows. This difference is statistically significant. Consistent with the previous relationship being less pronounced for loan pricing, there is no discernible difference in terms of offered interest rate. These results suggest that using cashless payments for spending may reveal a low likelihood of diverting cash flows, for instance, towards personal usage, or even discipline such behavior. Applicants are likely to have more control over cashless payment use for outflows, and thus this choice is more revealing of their creditworthiness.

4.2 Informational Precision of Payment Records

We next investigate whether the use of cashless payments with higher informational precision predicts more pronounced improvements in financing outcomes. The granularity of our data and the classification of payment technology in terms of information intensity allow us to do so.

[19] The prospect of repeat applicants naturally arises concerns that borrowers may learn to optimize their behaviors around a particular FinTech lender's credit model. However, we believe that two features in our setting mitigate these concerns. First, the credit model used by our FinTech lender is undisclosed, which makes it difficult for borrowers to understand the process well enough to game the system. This fact is especially true when operating with relatively novel technology like cashless payments. Second, the class of borrowers who use Indifi do not fit the typical profile of sophisticated borrowers who game the system.

We separate the share of cashless payments into the share of information-intensive technologies and information-light technologies. Information-intensive technologies correspond to payments that are not aggregated and whose counterparty type or identity can be easily identified. These information-intensive payment technologies therefore generate payment records with a larger informational content.

We repeat the baseline specification (3.1) while focusing on cashless payments with high informational precision. Panel B of Table 5 reports the results. A higher share of information-intensive payments is associated with a higher likelihood of loan approval, a lower interest rate conditional on loan approval, and a higher loan amount. These coefficients have larger economic magnitudes compared to their counterparts in Table 2, which supports a stronger relationship when focusing on cashless payments with high informational precision.[20] This result further supports the informational channel underlying the relationship between cashless payments and financing outcomes.

4.3 Introducing Applicant Fixed Effects

While our rich data allow us to control for virtually any observable characteristic that the lender can screen on, one might still be concerned that a lack of granularity for such controls or econometric limitations of our regression model leave room for unobserved variable bias. To mitigate this concern, we restrict our sample to repeat applicants and run a specification that includes applicant fixed effects, relying on within-applicant time-series variation in cashless payment usage. Such a specification absorbs any time-invariant characteristics that could be correlated with cross-sectional usage of cashless payments. We focus on the extensive margin, as repeat successful borrowers are significantly fewer than repeat applicants, and we control for time fixed effects and credit score trajectories, to ensure that a general time trend in cashless payment adoption or applicant improvement in creditworthiness does not drive our results.

[20] One concern with this interpretation is that the breakdown of payment technologies proxies for unobserved characteristics that relate to borrower creditworthiness, such as having a certain business model or targeting a specific customer population. While the industry and zip code fixed effects mitigate this concern, it cannot be completely ruled out.

Specifically, we run the specification

$$Approved_i = \beta CashlessShare_{i,t} + \mu_i + \delta_t + Score_{i,t} + \varepsilon_i \, , \tag{4.3}$$

where $Approved_i$ is an indicator variable for the loan application being approved, $CashlessShare_i$ is the standardized share of cashless payments measured over the six-month period prior to an application, μ_i are applicant fixed effects, δ_t are application month-year fixed effects, and $Score_{i,t}$ is the credit score of the business owner at the time of a given application. Results are displayed in table 6. We find that a within-applicant-firm increase in cashless payment usage is associated with a significant increase in the likelihood of being approved for a loan. This finding significantly reduces concerns about unobserved variable bias driving our main results. We therefore conclude that cashless payment usage contains information that is uniquely valuable in assessing creditworthiness.

[Insert Table 6 here]

4.4 Cashless Payments, Firm Quality, and Financing Outcomes

We now investigate whether cashless payment usage substitutes or replaces other signals of firm quality. We find that it acts as a complement, consistent with its distinct nature compared to usual quality signals. To this end, we interact the standardized share of cashless payments with proxies for firm quality in our baseline specifcation, again using the full set of controls and fixed effects:

$$\begin{aligned} FinancingOutcomes_i &= \beta_1 CashlessShare_i + \beta_2 FirmQuality_i \\ &+ \beta_3 CashlessShare_i \times FirmQuality_i + \gamma X_i + \sum_k \theta_{F_k(i)} + \varepsilon_i \end{aligned} \tag{4.4}$$

We use two proxies for firm quality that are based on different information: the owner's credit score, and the volatility of payment outflows, which we calculate from the payment records.

Panel A of Table 7 reports the results. The regression coefficients on the interaction term show that for firms whose owner has a higher credit score, a higher share of cashless payments leads to an even higher likelihood of loan approval, a lower offered interest rate conditional on loan approval, and a higher loan amount, compared to firms with a lower credit score. These results suggest a stronger benefit of using cashless payments for firms with a better type, consistent a complementarity between the information provided by cashless payment records and other sources of information that are useful for assessing creditworthiness.

[Insert Table 7 here]

To shed light on the value of the information contained in payment records beyond cashless payment usage, we construct a complementary signal for firm quality based on the content of payment records, namely, the weekly volatility of payment outflows, which proxies for firm default risk.[21] We again interact the standardized share of cashless payments with this proxy for firm quality, using specification (4.4), with the full set of controls and fixed effects, including credit score band fixed effects. Results are presented in Panel B of Table 7. We again observe a complementarity between cashless payment usage and the empirical proxy for firm quality for both the extensive and intensive margins of screening, as well as for predicting defaults. Internet Appendix Table A10 presents similar results using weekly inflow volatility.

5 Instrumental Variable Analysis

To strengthen the causal interpretation of our previous results, we use the 2016 Indian Demonetization and the granularity of our data to conduct instrument variable analysis. The main motivation for this analysis is to further address concerns over unobserved variable bias, including applicant time-varying characteristics, which would weaken the case for our favored interpretation of the empirical results. By identifying from a plausibly exogenous shock to the use of cashless payments, we can pin down that FinTech lenders incorporate cashless payment usage in their screening decision. Further, an additional interpretation of the causal evidence provided by this analysis is that cashless payment adoption affects loan outcomes by impacting applicants, in the sense that even "forced" adoption of cashless

[21] Using inflows provides qualitatively comparable results. Note that many more proxies for firm quality can be built from the payment record, but the goal of our analysis is to provide one representative complementary signal for firm quality based on the context of payment records, rather than to fully recover the lender's screening model.

payments will have a disciplining effect on applicants, increasing their creditworthiness. This analysis also strengthens the claim for complementarity of the information derived from cashless payment usage with other signals by instrumenting the interaction between cashless payment usage and credit score.

5.1 Identification Strategy

We instrument the share of cashless payments with an indicator variable for banking at a currency chest bank branch interacted with an indicator variable for the years in which cash shortages resulting from the Demonetization were particularly pronounced. Because such shortages of cash following the Demonetization were less intense at currency chest branches, their clients should rely relatively more on cash and less on cashless payments, compared to those who do not bank with a currency chest branch, all else equal. Our instrument variable is inspired by and adapted from Chodorow-Reich et al. (2020) and Crouzet, Gupta, and Mezzanotti (2023), who use cross-district variation in the number or activity of currency chest branches to identify the effects of the 2016 Indian Demonetization on payment choices and other broader economic outcomes. Compared to their identifying strategy, a strength of our approach is that we derive identification from within-district variation in treatment, which is enabled by the granularity of our data. This level of variation particularly suits our goal of studying the use of cashless payments on financing outcomes at the loan application level because cross-district variation could be correlated with local economic conditions unrelated to individual applicant payment technology, which would likely violate the exclusion restriction of our instrument.

The key identifying assumption underlying our instrument is that the matching between an applicant firm and a currency chest branch at the time of the cash shortages is orthogonal to firm quality that is used by the lender but not adequately controlled for in our regressions. This assumption about credit demand is likely satisfied for several reasons. First, we observe the same and full information set as the lender does and control for it nonlinearly. Second, the designation of currency chest status is at the branch level, while endogenous matching between firms and banks, if present, is more likely to happen at the bank level. Third, the Demonetization was unexpected, while banking relationships are known to be sticky due to high switching costs, which further mitigates concerns about the existence of endogenous bank-firm matching driven by the Demonetization. In addition, such a selection would be problematic for our interpretation only if firms of unobservably low quality intentionally change their banking relationship and match with currency chest bank branches in response to the Demonetization, which is unlikely.[22] As shown in Table A11 in the Internet Appendix, firms that bank at a currency chest branch are comparable to those that do not along various dimensions regarding firm fundamentals.

A final threat to identification is that cash shortages may affect credit supply differentially at the branch level, for instance, if currency chest branches can better maintain their credit supply activity, a potential violation of the exclusion restriction of our instrument. Our analysis, however, is immune to this concern because we are studying outcomes for FinTech loan applicants only. We focus on the relationship between loan approval by the FinTech lender and cashless payment use, which is plausibly orthogonal to branch-level credit supply, as opposed to other alternative outcomes such as, for instance, the number of applications the FinTech lender receives from firms banking at a given branch or the take-up of FinTech loans.

5.2 Results

We illustrate the first stage of our instrumental variable in Figure 3, Panel A, by plotting the unconditional mean cashless share for applicants banking at a currency chest branch and at other bank branches. We find that applicants banking at currency chest branches in 2018 and 2019 exhibit lower usage of cashless payments, consistent with their better access to cash. In Panel B, we plot the regression coefficients obtained when regressing the cashless share on the interaction between an indicator variable for banking at a currency chest branch and year fixed effects, controlling for our standard set of applicant characteristics. This exercise confirms the validity of our first stage. The magnitude is also large, as the reduction in cashless payments is around 10 percentage points.

[Insert Figure 3 here]

We next present results of a two-stage least squares (2SLS) regression in Table 8. We

[22] Whether a bank branch is a currency chest branch is not marketed as a public feature, and most borrowers do not know if they bank at a currency chest branch or not. There are also no clear direct benefits from banking at a currency chest branch.

focus on loan approval, that is, the extensive margin of financing outcomes, as the dependent variable for this analysis.[23] We present the first-stage coefficient in columns (1) and (2), where column (1) only controls for a general trend by including year fixed effects, and column (2) includes the comprehensive set of fixed effects used in our main specifications. Consistent with Figure 3, we find that banking at a currency chest branch during 2018 and 2019, when cash shortages were pronounced, predicts significantly lower use of cashless payments, while doing so overall does not if we fully control for applicant characteristics. The Montiel Olea-Pflueger effective F-statistics for the first stage are above the critical value for rejecting weak instruments (Andrews, Stock, and Sun, 2019).

The second stage of our analysis is reported in columns (3) to (5), where we present a parsimonious specification in column (3), include the comprehensive set of fixed effects in column (4), and interact the instrumented share of cashless payments with the applicant credit score in column (5). The second-stage result in columns (3) and (4) is directionally consistent with the baseline OLS results: based on the plausibly exogenous variation in the use of cashless payments at the applicant level, we find that greater use of cashless payments leads to a significantly higher likelihood of loan approval. In terms of magnitude, the instrument estimate is larger than the OLS estimate: a one-standard-deviation increase in cashless payment use results in a 12% increase in the likelihood of getting a loan. This larger magnitude suggests that unobserved variable bias, or measurement error, is biasing our OLS estimate downward.[24] Column (5) strengthens the case for a complementarity between cashless payment usage and other signals of creditworthiness such as credit scores. The coefficient on the instrumented interaction term between cashless payment share and credit score is indeed consistent with that from the OLS, which mitigates concerns about the result from Table 7 being driven by a correlation between the two signals. For robustness, we also split our sample between business-to-customer (B2C) and business-to-business (B2B) industries and reproduce our 2SLS specification. Results are reported in Table A12 in the

[23]We lose statistical power in the first stage if we restrict the sample to successful applicants, as needed to study intensive margin outcomes. Because the instrument is an indicator variable rather than continuous, having a large sample is critical to obtain sufficient statistical power. The lender actively screening at the extensive margin on cashless share also reduces the variation in the instrument in the resulting sample.

[24]This magnitude should be interpreted with caution, however, as the local average treatment effect might be inflated compared to the true average treatment effect if firms with specific unobservable characteristics have better access to cash at currency chest bank branches.

Internet Appendix and are consistent across the two samples. In additional robustness checks, Table A13 replicates our results when the time period is restricted to the period after Demonization but without the time interaction, and Table A14 replicates our results with standard errors clustered at a three-digit zip-code level.

[Insert Table 8 here]

6 Model

To better understand the economic mechanism through which borrowers' use of cashless payments (independent of the information content) facilitates FinTech lending, we develop a simple theoretical framework that builds on Parlour, Rajan, and Zhu (2022). This model reconciles our empirical findings with each other and further establishes connections between these findings and pivotal elements of open banking and data privacy. The proofs are in Appendix B.

6.1 Setup

We consider two types of risk-neutral agents: a continuum of entrepreneurs and a competitive lender. The model unfolds over three dates: $t = 0, 1, 2$. The period between $t = 0$ and $t = 1$ is termed the "production stage," and the period between $t = 1$ and $t = 2$ is the "lending stage."

The entrepreneur possesses a risky production technology. Operating this technology requires a single unit of capital investment at time t. Its output at $t+1$ is governed by an i.i.d. Bernoulli random variable, $\tilde{\theta}$. Specifically, the technology yields θ upon success with probability $1 - \pi$ and zero upon failure with probability π. A failure can be interpreted as an instance in which the entrepreneur diverts capital for personal consumption. Here, π captures the likelihood of such diversions. Entrepreneurs are classified as "good" or "bad," with failure probabilities of π_G and π_B, respectively, where $\frac{1}{2} \leq \pi_G < \pi_B < 1$.[25] While

[25] This assumption is consistent with the Indian context of FinTech lending promoting financial inclusion by serving subprime borrowers with a relatively low prior of success. This assumption ensures that the expected cost of using cashless payments rises when the cashless payment technology is more informationally precise, as shown later in cost specification (6.2) and condition (6.9). In Appendix C, we show that the assumption of $\pi_G \geq \frac{1}{2}$ can be dropped under an alternative yet slightly more restrictive specification of the informative structure underlying the cashless payment technology similar to that in He, Huang, and Zhou (2023).

entrepreneurs know their own type, the lender is uninformed. Good entrepreneurs represent a fraction α of the population, and bad ones $1-\alpha$. The mean failure probability is therefore defined as $\bar{\pi} = \alpha\pi_G + (1-\alpha)\pi_B$. To focus on economically interesting scenarios, we assume that both technology types generate nonnegative expected surplus, that is, $(1-\pi_B)\theta \geq 1$. At $t = 0$, the entrepreneur has n units of capital goods with a reservation value of zero. Consequently, she invests recurrently during the production stage and independently employs her technology a total of n times, resulting in a sequence of production outcomes $Y = \{y_i | y_i \in \{0, \theta\}, 1 \leq i \leq n\}$.

At the beginning of the production stage $t = 0$, the entrepreneur decides on a payment processing method. She can opt for cash, rendering the production outcomes Y unverifiable, or she can commit to a cashless payment technology. The latter documents production outcomes as verifiable payment records accessible by the lender during the lending stage.[26] The commitment and the free access of payment records in the model are consistent with our empirical context where the lender requires applicants to submit payment records. They are also consistent with the increasing practice of open banking, where FinTech lenders are increasingly able to gain access to payment data that is traditionally processed and stored in banks. The cashless payment technology, for each production outcome y_i, independently generates a payment record x_i:

$$\begin{aligned} &\Pr(x_i = \theta | y_i = \theta) = \Pr(x_i = 0 | y_i = 0) = q \qquad \text{and} \\ &\Pr(x_i = 0 | y_i = \theta) = \Pr(x_i = \theta | y_i = 0) = 1 - q\,. \end{aligned} \tag{6.1}$$

Here, the parameter $\frac{1}{2} \leq q \leq 1$ captures the informational precision of the cashless payment system, with $q = 1$ corresponding to perfect precision and $q = \frac{1}{2}$ to pure noise. The informational precision q can be mapped to different types of payment technologies and payment in different directions (inflows versus outflows), as we discuss below. The set of all verifiable payment records is then denoted by $X = \{x_i | x_i \in \{0, \theta\}, 1 \leq i \leq n\}$ at $t = 1$.

When entering the financing stage at $t = 1$, the entrepreneur, now running out of the capital good, seeks financing through a loan from the lender. The lender, having potential

[26] It's worth noting that while our model presents cash as wholly unverifiable, the distinction lies in the enhanced verifiability of cashless transactions. In practice, businesses might blend various payment methods with different verifiability levels. For instance, checks are more verifiable than cash but less so than online bank transfers.

access to the entrepreneur's payment records X, proposes two loan contracts: r_{cashless} and r_{cash}. Here, r represents the repayment the lender obtains in the case of success. The first contract is offered to entrepreneurs with cashless payment records, while the second is for those without such records.

By date $t = 2$, the entrepreneur either repays the loan or defaults (recall that a default happens when the technology fails, representing the entrepreneur diverting funds to herself at the expense of the lender). In the event of default, the lender receives nothing. However, if the defaulting entrepreneur had opted for cashless payments at $t = 0$ and subsequently acquired the r_{cashless} contract at $t = 1$, she incurs a loss of C. Specifically,

$$C = \phi \sum_{i}^{n} (\theta - x_i)\,, \tag{6.2}$$

where $\phi > 0$ is a parameter.

We motivate C as representing either expected monetary or reputational costs borne by the entrepreneur upon default. In essence, (6.2) suggests that entrepreneurs' production outcomes are benchmarked against the production capacity θ when using cashless payments (relative to cash usage). If larger and more deviations from θ are observed in the cashless payment records in the event of a loan default, the entrepreneur faces higher costs. This cost specification is further motivated by the context of India, where a defaulting borrower might be labeled by the lender as a "willful defaulter."[27] Such individuals could face legal repercussions or even be barred from accessing financial services in the future.[28] The transparency afforded by cashless payment records makes it more straightforward for our FinTech lender to detect and demonstrate borrower resource-diverting activities, supporting claims of willful default. Along this line, Appendix D provides a discussion of legal cases in India supporting the idea underlying the cost specification (6.2) that more observed discrepancies in cashless payment records have led to a higher chance of fraudulent fund-diverting activities being identified in court in the event of a default, which in turn implies higher monetary or reputational costs borne by the defaulter. In addition, a defaulting borrower with more observed discrepancies in cashless payment records may also

[27] The Reserve Bank of India categorizes a defaulter as "willful" if an individual or a company deliberately and knowingly defaults on repaying loans despite having the financial means to repay.

[28] See https://www.rbi.org.in/commonperson/English/Scripts/FAQs.aspx?Id=3459.

encounter more challenges when attempting to negotiate a loan extension with the lender, also captured by a higher cost C.[29]

6.2 Equilibrium Analysis

To illustrate how cashless payments affect lending outcomes, we focus on a separating equilibrium in which good-type entrepreneurs endogenously choose cashless payments, and subsequently $r_{\text{cashless}} < r_{\text{cash}}$. Suppose a borrower of type $j \in \{G, B\}$ accepts loan contract (r_{cashless}, C), his expected utility from the loan is given by

$$w_j(r_{\text{cashless}}, C|\pi_j) = (1-\pi_j)(\theta - r_{\text{cashless}}) - \pi_j \mathrm{E}_j[C] \,. \tag{6.3}$$

In contrast, if a borrower of type $j \in \{G, B\}$ accepts the other loan contract r_{cash}, her expected utility is then

$$w_j(r_{\text{cash}}|\pi_j) = (1-\pi_j)(\theta - r_{\text{cash}}) \,. \tag{6.4}$$

In a separating equilibrium, the competitive lender designs the two loan contracts (r_{cashless}, C) and r_{cash} subject to borrowers' incentive compatibility and individual rationality constraints. We normalize the reservation utility of the entrepreneurs to zero at the lending stage. Based on (6.3) and (6.4), a separating equilibrium requires

$$(IC_G) \quad (1-\pi_G)(\theta - r_{\text{cashless}}) - \pi_G \mathrm{E}_G[C] \geq (1-\pi_G)(\theta - r_{\text{cash}}) \,, \tag{6.5}$$

$$(IC_B) \quad (1-\pi_B)(\theta - r_{\text{cash}}) \geq (1-\pi_B)(\theta - r_{\text{cashless}}) - \pi_B \mathrm{E}_B[C] \,, \tag{6.6}$$

$$(IR_G) \quad (1-\pi_G)(\theta - r_{\text{cashless}}) - \pi_G \mathrm{E}_G[C] \geq 0 \,, \tag{6.7}$$

$$(IR_B) \quad (1-\pi_B)(\theta - r_{\text{cash}}) \geq 0 \,, \tag{6.8}$$

[29] We note that the cost specification (6.2) in the context of default does not account for the direct or privacy-related costs associated with adopting cashless payments. The direct costs of adopting cashless payments are arguably minimal, especially when weighed against the convenience they offer even in developing economies (see Dubey and Purnanandam, 2023, also in the context of India). In addition, consumers might have intrinsic privacy reservations or exhibit reluctance towards using cashless payment technologies. This reluctance exists irrespective of their creditworthiness being "good" or "bad" or their default status, but might stem from fears of potential data exploitation by sellers or lenders (Liu, Sockin, and Xiong, 2020). While the magnitude of such privacy concerns remains challenging to quantify (Chen et al., 2023, Tang, 2023), introducing these considerations could counterbalance the advantages of cashless payment adoption, a topic we leave for future research.

where (6.5) and (6.6) are the incentive compatibility conditions for the good and bad types, respectively, and (6.7) and (6.8) are their individual rationality constraints.

According to (6.1) and (6.2), we can calculate

$$\mathrm{E}_j\left[C\right] = \phi n \theta \left(1 - q - \pi_j + 2q\pi_j\right) \, , \tag{6.9}$$

which is important in understanding the role of cashless payment records in shaping the borrower's payment choice and in turn the lending outcomes. Intuitively, the expected cost $\mathrm{E}_j\left[C\right]$ rises with an increase in the number of established cashless payment records during the production stage (i.e., when n is larger). This higher cost results from a stricter benchmark for evaluating the entrepreneur in the event of a default. The expected cost also rises when the entrepreneur has a higher likelihood of failure and subsequent default (i.e., when π_j is greater). Moreover, when the cashless payment technology is more informationally precise (i.e., q is larger), the payment records offer a clearer picture of the entrepreneur's diversion activities.

Proposition 1. *A separating equilibrium with $r_{cashless} < r_{cash}$ exists when the following two conditions hold:*

i). The cost of establishing cashless payment records is intermediate such that the good-type entrepreneur finds it beneficial to do so while the bad-type does not:

$$\frac{\pi_B - \pi_G}{\pi_B(1-\pi_G)(1-q-\pi_B+2q\pi_B)} \leq \phi n \theta \leq \frac{\pi_B - \pi_G}{(1-\pi_B)\pi_G(1-q-\pi_G+2q\pi_G)} \, . \tag{6.10}$$

ii). The average quality of the pool of entrepreneurs is not too high such that it is not profitable for the lender to offer another contract in which all entrepreneurs are pooled:

$$1 - \bar{\pi} \leq \frac{1-\pi_G}{1+\phi n \theta \pi_G \left(1-q-\pi_G+2q\pi_G\right)} \, . \tag{6.11}$$

Proposition 1 shows that a separating equilibrium exists in that good-type entrepreneurs endogenously choose cashless payments and self-select into the loan contract (r_{cashless}, C), while bad-type entrepreneurs choose cash and self-select into the loan contract r_{cash}, where $r_{\text{cashless}} < r_{\text{cash}}$. Conditions (6.10) and (6.11) show the intuition: good entrepreneurs benefit from such selection and consequently a lower interest rate, but they also have to bear the potential cost of publicizing unfavorable past production outcomes upon default. This cost is even greater for bad entrepreneurs, deterring them from using the cashless payment technology in the first place. Such a separating equilibrium exists only if the average quality of applicant entrepreneurs, captured by the average success probability $1 - \bar{\pi}$, is not too good. Otherwise, the cost will exceed the benefits of selection, rendering the proposed separating contracts inferior to a pooling contract. Indeed, condition (6.11) is consistent with the fact that the credit quality of an average borrower in a developing economy like India is not too good and thus selection (rather than pooling) leads to more efficient lending outcomes. Formally, we define the relationship characterized by Proposition 1 as the selection effect.

Importantly, the selection effect is stronger the more borrowers use cashless payments, and when cashless payments are informationally more precise in revealing an entrepreneur's type. Specifically, assuming ϕ is not too large, comparative statics can readily demonstrate that the separating equilibrium is more likely to emerge when i) the entrepreneur establishes more cashless payment records before the lending stage (i.e., n is larger) and ii) the informational precision of the cashless payment technology is higher (i.e., q is larger). Intuitively, an increase in n or q bolsters the efficacy of cashless payments as an informational selection tool, thereby augmenting the feasibility of a separating equilibrium. Our empirical observations presented in Tables 2 and 3 corroborate this, indicating that firms with more cashless payment transactions secure better loan terms and exhibit a reduced likelihood of loan default. Moreoever, the comparative statics with respect to information precision q is particularly helpful for understanding our results in Table 5 concerning the effects of information-intensive payments and payment outflows. Compared to information-light payments, information-intensive payment records possess a higher q, due to their capacity to offer a more exact benchmark of a firm's production outputs. Compared to payment inflows, payment outflows are also more precise about the firm's type (and thus have a higher q) because borrowers have more discretion over payment technology for outflows, and because they can more precisely benchmark potential resource-diverting activities, which matter the most for a firm's downside risk and default probability.

The idea underlying the selection effect is reminiscent of the traditional collateral-based lending model, in which costly liquidation of collateral during a default serves as a selection mechanism (Dell'Ariccia and Marquez, 2006). Yet our model focuses on unsecured loans, introducing an important difference that the lender does not recover any collateral value. Instead, cashless payment records serve as a form of "digital collateral" because it is more costly for bad entrepreneurs to present them even though the lender cannot directly monitor borrowers' repayment behaviors or manage their subsequent payments. Consequently, the use of cashless payments effectively reveals the applicant entrepreneurs' types in equilibrium, allowing the lender to screen them. This mechanism complements recent studies by Parlour, Rajan, and Zhu (2022) and He, Huang, and Zhou (2023), where the authors focus on the direct information content of payment records enabled by open banking.[30] This idea is also related to the concept of instrumental privacy preferences as studied in Chen et al. (2023), where bad borrowers face a higher cost in revealing their types by using cashless payments.

Proposition 2 further implies that a better entrepreneur will benefit even more from a separating equilibrium in terms of getting better borrowing outcomes.

Proposition 2. *In a separating equilibrium, the improvement in financing outcomes enjoyed by the entrepreneur that adopts cashless payments is larger if their relative default probability is lower in the sense that*

$$\frac{d(r_{cash} - r_{cashless})}{d(\pi_B - \pi_G)} > 0\,. \tag{6.12}$$

We define the relationship characterized by Proposition 2 as the accuracy effect. When selection between good and bad entrepreneurs happens, competition in the lending market implies that the lender will compete for better entrepreneurs by offering lower interest rates. Intuitively, selection allows entrepreneurs to effectively reveal their types to the lender, and thus better entrepreneurs may further benefit from the use of cashless payments under lending competition. Specifically, the comparative statics (6.12) lends itself to an interaction-term interpretation: the benefits from possessing cashless payment records, namely, more likely loan approvals, more favorable interest rates, and larger loan amounts,

[30]Specifically, in Parlour, Rajan, and Zhu (2022), cashless payments are useful for the lender to update its belief about the borrower's type, while loan size serves as a selection mechanism. To focus on the use of cashless payments itself as a selection mechanism, we abstract from separately modeling loan size.

are more pronounced for better firms, ceteris paribus. This accuracy effect offers insights into the empirical observations in Table 7, where the credit score of the firm owner and the volatility of payment outflows can be interpreted as proxies for a firm's true type.

Although the accuracy effect relies on the lending market being competitive, perfect competition is not crucial in driving the results. In essence, the accuracy effect arises from the selection effect in that good entrepreneurs can stand out from bad ones by using cashless payments. This observation highlights the crucial role of cashless payments in helping reveal borrowers' creditworthiness and facilitate more efficient lending. In a cash economy, the lack of information revelation and the resulting adverse selection implies that good entrepreneurs cannot get the low interest rate they deserve despite the lending market being potentially competitive.

7 Discussion

Before concluding, we discuss how our findings and framework relate to some actively discussed subjects in the literature, delineate the scope of our study, and explore some alternative mechanisms that might reinforce the link between FinTech lending and cashless payments.

7.1 Digital Collateral, Open Banking, and Privacy

We highlight two key distinctions between posting payment records (or "digital collateral") and pledging traditional collateral. These differences shed light on the concepts of open banking and privacy, two burgeoning themes central to the evolution of FinTech lending and payments.

First, the FinTech lender cannot offset their losses in the case of default by seizing the collateral. In addition, Indifi, the specific FinTech lender in our study, cannot observe or withhold future payment inflows. Therefore, the informational role of using cashless payments as "digital collateral" that we document acts through screening rather than monitoring, as illustrated in Section 6.[31] In this sense, our study provides a compelling economic justification for advocating broader access to historical payment records. Indeed,

[31] We note that our notion of "digital collateral" is also different from that in Gertler, Green, and Wolfram (2024), in which the lender can digitally disable collateral such as solar panels or cellphones that back a loan without reprocessing collateral, thus better monitoring the borrowers.

relationship banks that process payments might deliberately impose barriers to such informational access to prevent competition from competing lenders operating similar screening technologies. This challenge motivates the regulatory efforts in promoting open banking, a direction embraced by numerous jurisdictions (see Babina et al., 2025).

Second, posting digital collateral potentially introduces privacy concerns, which are typically absent in the context of traditional collateral-based lending. This difference arises from the informational role of cashless payment records, which may inadvertently disclose sensitive borrower-specific details. Conversely, the screening role of traditional collateral hinges primarily on the tangible costs borne by the borrowers, which are orthogonal to privacy concerns. A comprehensive exploration of the privacy implications of cashless payment usage, akin to the in-depth analysis by Chen et al. (2023) and Tang (2023) in related data-sharing contexts, represents an interesting avenue for future research.

7.2 Alternative Mechanisms Linking Cashless Payments and Lending

Beyond serving an informational role in loan screening, cashless payments may be also useful in enabling lenders to continuously monitor borrowers and ensure loan repayment. In the United States, lenders such as PayPal and Square maintain continuous access to the ongoing payment flows of borrowers post-loan origination, providing them with an advantage in loan monitoring. Similarly, platform-enabled BigTech lenders, for example, Amazon and Alibaba, leverage this same advantage (Liu, Lu, and Xiong, 2022). Notably, several of these entities withhold a portion of the incoming payment flows to borrowers, directly allocating these funds towards loan repayment.[32] Theoretically, Huang (2023) studies how this feature allows FinTech lenders to screen borrowers and compete with traditional banks.

In the empirical framework of our study, the use of payments for loan monitoring or repayment collection is inherently restricted. The standard unsecured loans that we study do not have innovative repayment mechanisms. Furthermore, Indifi does not possess access to the continuous payment information of borrowers beyond a historical span of six months prior to the application date. Consequently, we focus on the screening role of cashless payments, leaving these other aspects for future research.

[32] Rishabh and Schaublin (2021) study how borrowers' behavior evolves after issuing such loans.

Another important connection between the adoption of cashless payments and the development of FinTech and BigTech lending relates to convenience, underscored in studies such as Fuster et al. (2019), Berg, Fuster, and Puri (2022), and Liu, Lu, and Xiong (2022). One plausible hypothesis regarding the simultaneous rise of cashless payments and FinTech lending is that they both result from a common demand for user convenience. We view our findings as both independent and complementary to this convenience-driven rationale for the following reasons.

First, convenience is tied to the demand side for both cashless payment and FinTech lending, while our study focuses on the supply side of lending, as we study loan application screening. One unique strength of our data is that we can flesh out supply from demand, as we observe applications, screening decisions, and applicant responses to offers. While for cashless payments our selection mechanism speaks to a potential force for technology adoption, we view it as nonmutually exclusive with a quest for convenience. We also view potential interactions between these two forces as an interesting avenue for future research.

Second, convenience might result from the integration of payments and lending in the same ecosystem, as, for instance, Alibaba does. The FinTech lender we study only offers loans, and does not bundle this credit product with any payment products. Nevertheless, the informational channel that we highlight provides a supply-side rationale in addition to convenience for bundling lending and payment products in the same ecosystem.

7.3 Cashless Payments and Financial Inclusion

The synergy between FinTech lending and cashless payments raises the question of whether an increase in the use of cashless payments may improve financial inclusion, by facilitating access to financing for applicants that were historically outside of the financial system due to informational frictions. While our empirical setting is not perfectly suited to study this question, as we do not observe lending outcomes outside of the FinTech lender, our results suggest that benefits in that regard might be limited.

We first note that while 12% of the applicants do not have previous credit activities, this share is even lower for the applicants that successfully get a FinTech loan: only 5% of them do not have previous credit activities. These numbers provide an upper bound to the benefit of the mechanism we study. Such limited room for impact is somewhat in contrast with contemporaneous studies by Agarwal et al. (2021), Di Maggio, Ratnadiwakara, and Carmichael (2021), and Ouyang (2023), who specifically focus on the financial inclusion implications of the use of alternative data. However, it is aligned with screening policies by prominent U.S. FinTech lenders such as Lending Club, which impose a minimum FICO score to be eligible for applying for a loan and therefore mechanically limit financial inclusion benefits. A possible reconciliation of both facts is that cashless payments typically require a bank account and therefore mostly benefit applicants that are at least partly included in the financial system. Meaningful effects at the intensive margin of financial inclusion could still be happening but would require more comprehensive data to document.

Further, our result on applicants with initially higher credit scores enjoying more pronounced improvement in financing outcomes (see Table 7) also suggests a form of market segmentation and a potentially nonmonotonic effect of FinTech lending on financial inclusion. If FinTech lenders are particularly competitive for high-quality borrowers that are previously served by banks, they may disproportionately gain market share in this high-quality segment relative to incumbent banks. The general equilibrium effect on access to credit will depend in turn on whether incumbent banks adjust by shifting their attention to previously unserved borrowers. We leave investigation of these more involved interactions between banks and FinTech lenders to future empirical studies.

7.4 Borrower Self-Selection between Different Types of Lenders

Related to the interaction between FinTech lenders and traditional banks mentioned above, it is natural to expect some level of self-selection of applicants between these two types of lenders. Our empirical setting, however, is not suited to examining this potential self-selection, as it does not include bank credit data. The sample of applications that we observe is not necessarily representative of the overall pool of small businesses seeking unsecured credit. For example, firms with better payment records may be more likely to apply for FinTech credit. While a formal analysis of such self-selection dynamics remains beyond our capacity, their possible existence does not diminish our primary conclusions regarding the informational role of cashless payments on lending outcomes. In fact, the potential presence of self-selection is consistent with the selection effect we flesh out in

Section 6. Moreover, the potential competition between FinTech lenders and traditional banking institutions is in line with our model's assumption of a lender operating in a competitive credit market. Note that our data having both approved loans and rejected loan applications already takes a step forward compared to prior literature in which most lending data include only approved loans but not applications. We leave the test on endogenous application to future research as more data become available.

8 Conclusion

Our study documents an informational synergy between cashless payments and FinTech lending. The use of cashless payments translates into improved access to capital from FinTech lenders. In the context of unsecured lending to small businesses in India, we find that higher usage of cashless payments yields a higher likelihood of obtaining a loan, reduced interest rates, and larger loan amounts. Cashless payment usage also predicts a lower likelihood of default. We interpret these empirical results as consistent with signaling and disciplining roles of cashless payment use.

As cashless payments continue to rise in prominence and accessibility across the globe, our research underscores the unique value of payment records as rich sources of information for evaluating borrowers' creditworthiness and for making financial intermediation more efficient. Our study carries broader implications for the financial sector, providing a powerful rationale for FinTech and BigTech platforms combining payments and lending, as well as for open banking.

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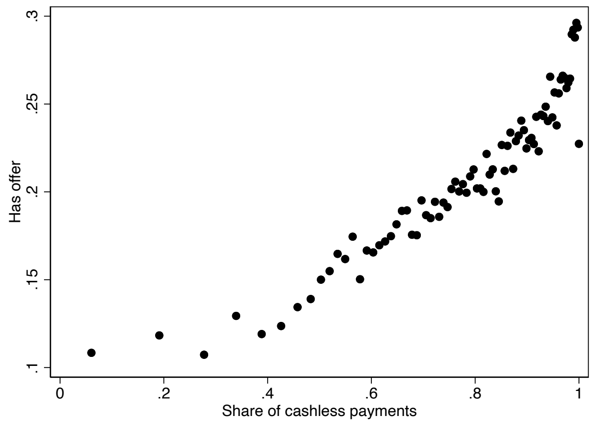
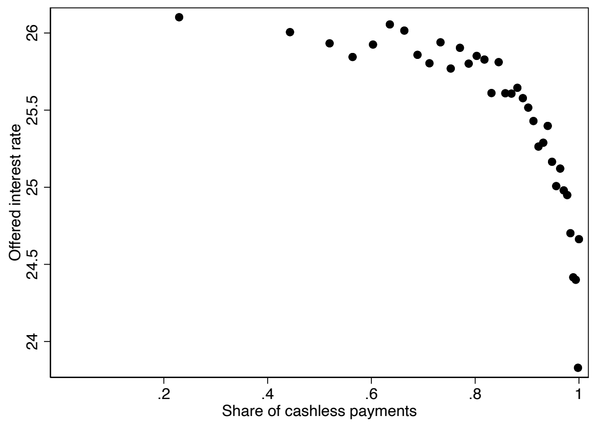
Figure 1: **Share of cashless payments and financing outcomes**

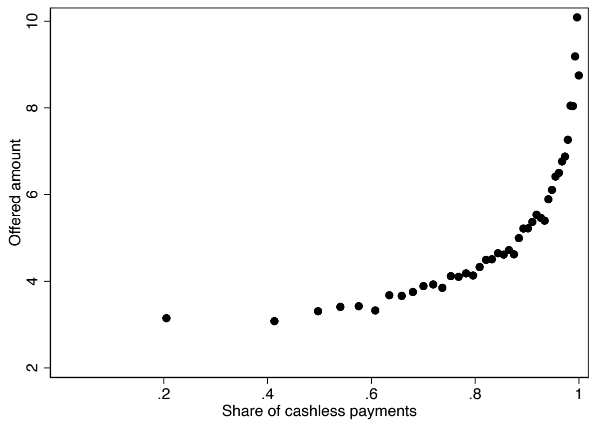
Panel A. Loan Approval



Panel B. Offered Interest Rate

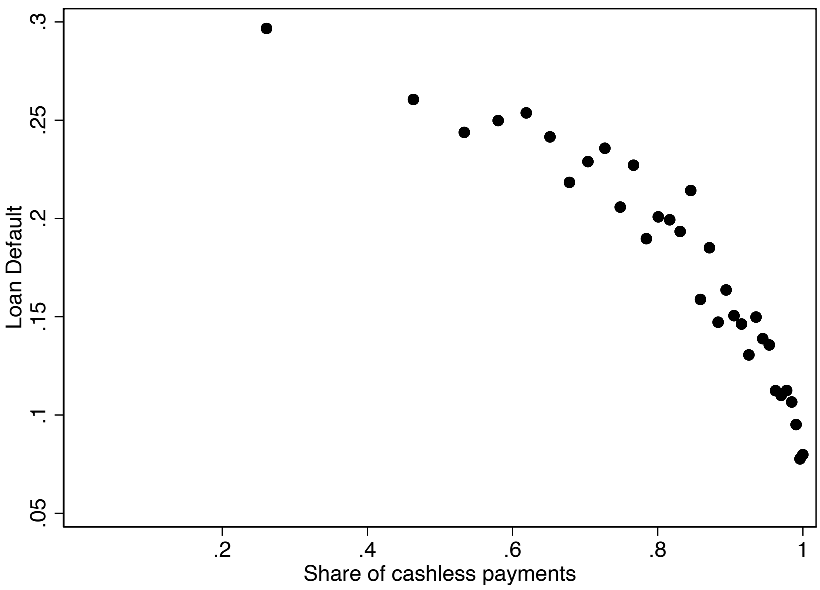


Panel C. Offered Amount



This figure presents binned scatter-plots of the share of cashless payments and of various loan characteristics. Panel A has an indicator for whether a loan is approved on the y-axis. Panel B has the offered interest rate on the y-axis. Panel C has the offered loan amount in units of Indian Lakh (1 Lakh = 100,000 rupees). The share of cashless payments is defined in Section 2.2.

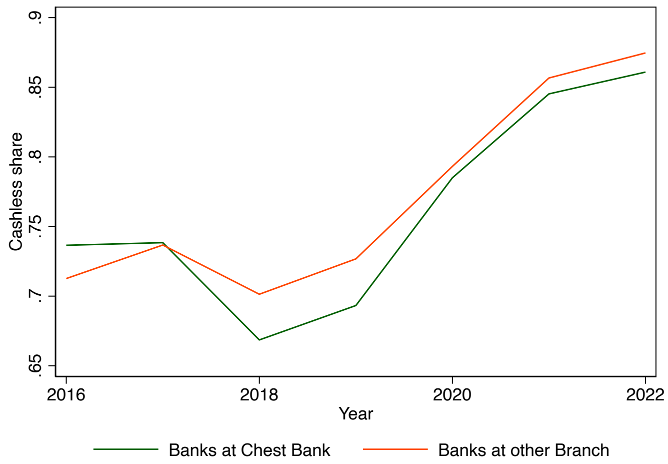
Figure 2: **Share of cashless payments and loan default**



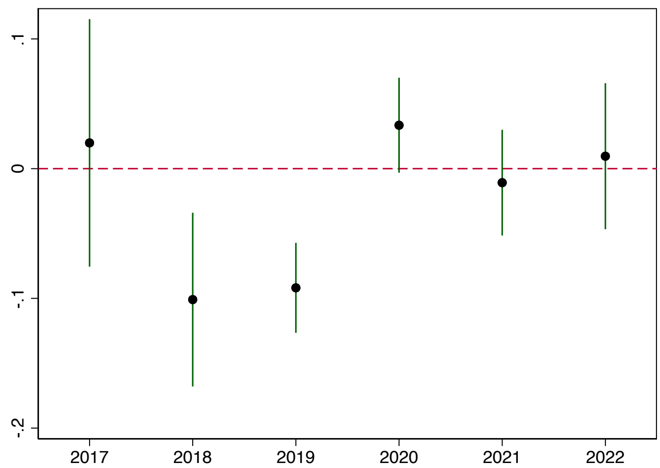
This figure presents a binned scatter-plot of share of cashless payment and an indicator for loan default.

Figure 3: **Share of cashless payments and banking at a currency chest bank branch**

(a) Panel A. Unconditional Cashless share



(b) Panel B. Event-Study Regression Coefficients



Panel A plots raw cashless share (yearly mean) for firms banking with chest bank vs. non-chest banks at yearly frequency. Panel B plots the regression coefficients and corresponding confidence intervals of share of cashless share on the interaction of year and an indicator of if firms bank at a chest bank.

Table 1: **Summary Statistics**

	Obs	**Mean**	**Std Dev**	**p25**	**p75**
		Panel A. Loan Applicant Characteristics			
Year of Application	316,719	2020	1.4	2019	2021
Applicant Age	314,890	36.6	9.3	29.8	41.8
Business Age	316,719	4.3	4.6	2.0	5.0
Credit History Length (in Years)	281,966	7.7	5.8	3.0	12.0
Cibil Score	279,860	693	117	676	749
Missing Cibil Score (0/1)	316,719	0.116	0.320	0	0
Top-up Loan (0/1)	316,669	0.149	0.356	0	1
		Panel B. Payment Records			
Share of Cashless Payments	316,407	0.779	0.202	0.668	0.940
of which: Information-intensive Payments	316,407	0.528	0.273	0.320	0.749
Share of Cashless Inflows	316,121	0.775	0.263	0.640	0.988
Share of Cashless Outflows	314,539	0.783	0.272	0.678	0.990
Share of Cash Payments	316,407	0.221	0.202	0.060	0.332
Share of Revenues from Online Marketplace	31,194	0.324	0.289	0.095	0.475
Borrower Banks at Chest Bank Branch (0/1)	316,719	0.036	0.187	0	0
Avg. Monthly Revenue (INR)	316,719	1,379,202	9,030,443	147,459	919,192
Avg. Monthly Balance (INR)	316,698	35,025	132,948	10,236	71,199
Avg. # of Transactions	316,719	738	1469	201	824
Weekly Outflow Volatility	316,560	0.05	0.06	0.02	.06
		Panel C. Loan Application Outcomes			
Approved Loan (0/1)	316,719	0.208	0.406	0	0
Offered Interest Rate (%)	66,018	25.4	4.0	24	28
Offered Maturity (month)	66,017	20.2	9.5	12	24
Offer Amount (INR)	66,017	535,339	730,438	200,000	600,000
Disbursed (0/1)	66,017	0.623	0.485	0	1
Default (0/1)	41,123	0.175	0.380	0	0

This table reports summary statistics for the main variables used in the regressions. The sample consists of all complete applications to Indifi between September 2015 and September 2022. Panel A reports summary statistics for loan applicants by application year, age, credit score, and credit history. Panel B displays summary statistics for payment records, obtained through disaggregation of bank statements, and covers payment technologies, bank type, monthly average revenue, monthly average balance, and weekly outflow volatility. Weekly outflow volatility is defined as standardized weekly spending over monthly spending. Panel C reports summary statistics for financing outcomes of the applications.

Table 2: **Cashless Payments and Financing Outcomes**

	Approved Loan (1/0)		Offered Interest Rate		log(Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of cashless payments	0.020***	0.017***	-0.493***	-0.440***	0.143***	0.134***
	(0.001)	(0.001)	(0.024)	(0.024)	(0.006)	(0.006)
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	No	Yes
3-digit zipcode FE	No	Yes	No	Yes	No	Yes
Revenue deciles FE	No	Yes	No	Yes	No	Yes
Observations	314,538	311,942	65,983	65,941	65,980	65,938
R^2	0.168	0.218	0.246	0.281	0.322	0.349

This table presents coefficients from OLS regressions that regress an indicator for having a loan application approved (column (1) and (2)), the loan interest rate offered (column (3) and (4)), and the loan amount (column (5) and (6)), on the share of cashless payments. The share of cashless payments is calculated as per Section 2.2 and is then standardized. The set of borrower controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. There are 67 industries. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. 3-digit zipcode is the first three digits of the Indian Pincode. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: **Cashless Payments and Default**

	Loan Default (1/0)				Days to First Delinquency		Days to Full Repayment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of cashless payments	-0.021***	-0.023***	-0.020***	-0.022***	5.229*	2.577	-6.661***	-12.000***
	(0.003)	(0.003)	(0.003)	(0.003)	(2.663)	(2.890)	(2.143)	(2.152)
Interest Rate (Log)			0.058***	0.046***				
			(0.010)	(0.009)				
Amount (Log)			0.005*	0.004				
			(0.003)	(0.003)				
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	No	Yes	No	Yes
3-digit zipcode FE	No	Yes	No	Yes	No	Yes	No	Yes
Revenue deciles FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	41,261	41,227	41,261	41,227	7095	6751	23,541	23,129
R^2	0.125	0.149	0.126	0.150	0.201	0.258	0.250	0.290

Columns (1) to (4) present coefficients from OLS regressions that regress loan default on the share of cashless payments. Columns (5) and (6) present coefficients from OLS regressions that regress the time from loan inception until first delinquency (in days) on the share of cashless payments. Columns (7) and (8) show the coefficients for time from loan inception until full repayment (in days) regressed on the share of cashless payments. The regressions in columns (5) to (8) are run by Indifi due to regulatory restrictions. The share of cashless payments is calculated as per Section 2.2 and is then standardized. The set of borrower controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. There are 67 industries. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. 3-digit zipcode is the first three digits of the Indian Pincode. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: **Alternative Transaction Record and Financing Outcomes**

	Approved Loan (1/0) (1)	Offered Interest Rate (2)	log(Amount) (3)	Default (1/0) (4)
Share of online marketplace transactions	0.061***	-0.325***	0.034***	-0.006***
	(0.002)	(0.038)	(0.005)	(0.001)
Share of cashless payments	0.016***	-0.453***	0.131***	-0.018***
	(0.001)	(0.026)	(0.006)	(0.002)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Interest rate FE	No	No	Yes	Yes
Observations	311,942	65,942	65,939	65,942
R^2	0.216	0.211	0.343	0.088

This table presents coefficients from OLS regressions that regress an indicator for having a loan application approved (column (1) and (2)), the interest rate offered (column (3) and (4)), and the loan amount offered (column (5) and (6)), on the standardized share of revenues originating from an online marketplace that has a data-sharing agreement with Indifi. The share of revenues from the online marketplace is calculated as the average monthly revenue on the partner online marketplace divided by the average total monthly revenue as per the banking statements and is then standardized. The share of information-intensive payments and the share of information-light payments are calculated as per Section 2.2 and are then standardized. The set of controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. There are 67 industries. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. 3-digit zipcode is the first three digits of the Indian Pincode. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: **Cashless Payments and Financing Outcomes: Informational Content**

	Approved loan (1/0)		Offered interest rate		log (Amount)		Loan Default (1/0)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Cashless Inflows and Outflows								
Share of Cashless Inflows	0.008***	0.007***	-0.368***	-0.320***	0.077***	0.068***	-0.009***	-0.011***
	(0.001)	(0.001)	(0.023)	(0.022)	(0.006)	(0.006)	(0.002)	(0.002)
Share of Cashless Outflows	0.022***	0.019***	-0.357***	-0.340***	0.150***	0.144***	-0.021***	-0.020***
	(0.001)	(0.001)	(0.022)	(0.023)	(0.005)	(0.005)	(0.002)	(0.002)
Observations	312,310	309,744	65,670	65,628	65,667	65,625	65,670	65,628
R^2	0.169	0.219	0.247	0.282	0.327	0.354	0.074	0.091
Panel B. Cashless Payment Information Quantity								
Share of information-intensive payments	0.050***	0.042***	-0.708***	-0.637***	0.274***	0.272***	-0.017***	-0.014***
	(0.002)	(0.002)	(0.035)	(0.036)	(0.005)	(0.006)	(0.002)	(0.002)
Observations	314,537	311,941	65,983	65,941	65,980	65,938	65,983	65,941
R^2	0.179	0.226	0.259	0.291	0.368	0.395	0.073	0.089
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	No	Yes	No	Yes
3-digit zipcode FE	No	Yes	No	Yes	No	Yes	No	Yes
Revenue deciles FE	No	Yes	No	Yes	No	Yes	No	Yes

This table presents coefficients from OLS regressions that regress the dependent variables used in the previous tables on the share of cashless payments in inflows and outflows (Panel A), and on the share of information-intensive payments (Panel B), as defined in Section 2.2. The definition for share of information-intensive payments is described in Section 2.2. These dependent variables are standardized. The set of controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. 3-digit zipcode is the first three digits of the Indian Pincode. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: **Repeat Loan Applicants**

	Approved Loan (1/0)			
	(1)	(2)	(3)	(4)
Share of cashless payments	0.014***	0.009***		
	(0.001)	(0.003)		
Share of cashless revenue			0.002	
			(0.003)	
Share of cashless spending			0.010***	
			(0.002)	
Share of information-intensive payments				0.021***
				(0.003)
Borrower FE	No	Yes	Yes	Yes
Borrower Time Varying Controls	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
Observations	154,485	154,485	153,330	154,485
R^2	0.201	0.583	0.583	0.583

This table presents coefficients from OLS regressions that regress an indicator for having a loan application approved. The sample is restricted to top-up loans. All variables, borrower controls, and fixed effects are constructed as specified in previous tables. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: **Complementarity with Other Signals**

Panel A. Cibil score

	Approved Loan (1/0) (1)	Offered Interest Rate (2)	log(Amount) (3)	Default (4)
Share of cashless payments	0.023***	-0.432***	0.125***	-0.020***
	(0.001)	(0.023)	(0.007)	(0.002)
Cibil Score	0.050***	-0.421***	0.138***	-0.013***
	(0.004)	(0.031)	(0.005)	(0.002)
Share of cashless payments × Cibil Score	0.012***	-0.219***	0.039***	0.002
	(0.001)	(0.032)	(0.005)	(0.003)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	277,323	62,445	62,442	62,445
R^2	0.171	0.191	0.330	0.086

Panel B. Variables from payment record

	Approved loan (1/0) (1)	Offered interest rate (2)	log (Amount) (3)	Default (4)
Share of cashless payments	0.018***	-0.425***	0.130***	-0.001***
	(0.001)	(0.023)	(0.006)	(0.000)
Weekly outflow volatility	-0.001	0.060	-0.036***	0.001
	(0.003)	(0.040)	(0.010)	(0.000)
Share of cashless payments × Weekly outflow volatility	-0.002***	0.155***	-0.041***	0.001***
	(0.000)	(0.020)	(0.005)	(0.000)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	311,938	65,942	65,938	311,938
R^2	0.218	0.281	0.350	0.035

Panel A presents coefficients from OLS regressions that regress an indicator for having a loan application approved (column (1)), the loan interest rate offered (column (2)), the loan amount (column (3)), and default (column (4)) on the share of cashless payments and the Cibil score. Both dependent variables are standardized. The sample is restricted to observations that have a Cibil score. Panel B regresses the same dependent variables on the share of cashless payments and weekly outflow volatility. Weekly outflow volatility is defined as weekly spending over monthly spending. This term is both standardized and winsorized. The set of borrower controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. There are 67 industries. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. 3-digit zipcode is the first three digits of the Indian Pincode. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: **IV: Cashless Payment Use and Loan Approval**

	Share of cashless payments		Approved Loan (1/0)		
	(1)	(2)	(3)	(4)	(5)
Share of $\widehat{\text{cashless}}$ payments			0.148**	0.117*	0.125*
			(0.066)	(0.064)	(0.069)
Share of $\widehat{\text{cashless}}$ payments × Cibil Score					0.056***
					(0.013)
Chest in 2018 or 2019	-0.125***	-0.108***			
	(0.020)	(0.020)			
Borrower banks at Chest Bank (1/0)	-0.044***	0.013	-0.016**	-0.009*	-0.007
	(0.012)	(0.013)	(0.008)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Application month FE	No	Yes	No	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	Yes
3-digit zipcode FE	No	Yes	No	Yes	Yes
Revenue deciles FE	No	Yes	No	Yes	Yes
Observations	316,407	311,941	316,407	311,941	275,889
F-statistic	37.41	26.90	-	-	-

This table presents regression coefficients for a 2SLS specification. We present the first-stage coefficients in columns (1) and (2), where we regress the share of cashless payments on the instrument defined as the interaction between an indicator variable for banking at a currency chest branch and an indicator variable for the application happening in 2018 or 2019. Column (1) only controls for an indicator variable for banking at a currency chest branch, as well as yearly fixed effects. Column (2) runs the same analysis with additional fixed effects. The second stage of our analysis is presented in columns (3) to (5), where we regress an indicator variable for the application being approved on the instrumented share of cashless payments. Column (3) controls for an indicator variable for banking at a currency chest branch, as well as yearly fixed effects. Column (4) runs the same analysis with additional fixed effects. Column (5) additionally interacts the instrumented share of cashless payments with the applicant's Cibil score, keeping the same comprehensive fixed effects. The share of cashless payments is calculated as per Section 2.2 and is then standardized. The set of borrower controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. There are 67 industries. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. 3-digit zipcode is the first three digits of the Indian Pincode. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. The reported F-statistic is the 'Effective F-Stat' as described in Montiel Olea and Pflueger (2013). Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix

A Classification of Payment Records

In this appendix, we provide a detailed elaboration of the method by which we classify identifiable payment records into cash or cashless payments, as well as between information-intensive cashless payments and information-light cashless payments.

To start, we identify and classify cash payments. Payment records with strings "cash withdrawal," "cash deposit," "ATM withdrawal," "ATM deposit," and associated variations are identified and classified as cash payments.

We then identify and classify cashless payments, proceeding by technology.

For Internet banking payments, we identify and classify six sub categories. First, payments made by Immediate Payment Service (IMPS), which is the instant payment interbank electronic funds transfer system in India, are identified by a description including strings "INB IMPS" or "ONL IMPS." Second, Internet banking transactions on banks' websites are identified by the relevant strings, including large corporate transfers and any transfers between saving/checking accounts. Third, direct deposits are identified by the relevant strings, including loan disbursals, salary, investment income, etc. Fourth, online payments made by debit cards are identified by the string "purchase by card." Fifth, Mastercard Money Transfer is identified by a description that starts with "MMT." Finally, automatic fee deduction (excluding bank charges) and automatic payments (loan repayments, utilities, credit card repayment, etc.) are identified by the relevant strings.

For certified check payments, they are identified by a description including "CLG-CHQ," "ECS/ACH," "Cheque," or that starts with "CLG."

For mobile payments, we identify and classify five subcategories. First, payments made through third-party mobile gateways, including Paytm, Razorpay, PayU, Phonepe, and Paypal, are identified by the relevant strings. Second, mobile banking payments made through mobile banking apps are identified by a description starting with "MB," "MOB/TPFT," "MOBFT" or including "PayZapp." Third, RuPay, which are payments made over texts, are identified using the relevant string. Fourth, payments made through Unified Payments Interface (UPI), a mobile payment system developed by India's National

Payment System for interactions between two bank accounts over mobile platforms, are identified by a description with "UPI." Finally, payments made through IMPS Mobile Transactions, another mobile system developed by India's National Payment system, are identified by a unique seven-digit "Mobile Money Identifier" (MMID).

For POS machine payments, they are identified by a description including "POS," "ECOM," or "PUR."

All of these payments above are classified as cashless payments. We then allocate technologies between information-intensive and information-light categories. We include Internet banking payments and certified checks in this category. In the context of India, those two broad payment technologies are information-intensive in the sense that each payment record corresponds to a single transaction (i.e., not aggregated), and the name and type of the payment counterparty is identifiable in the record.

We then identify information-light payments as payments through third-party mobile applications and mobile banking, as well as POS machine payments. In India, those payment records are either aggregated in bank statements or lack the name or type of the payment counterparty.

We finally note three adjustments and exceptions to the classification procedure above. First, the payment counterparty is not identifiable for a small number of Internet banking payments and certified checks in our sample, which we instead classify as information-light payments. Second, any cash transfer to electronic wallets on third-party mobile apps is classified as information-light cashless payments. And third, rejected payments and penalty charges due to rejected payments, whenever identified, are not classified as cash or cashless payments because they are indicative of technical errors in the payment process and do not fall into our economic framework.

Following the procedure described above, we are able to identify and classify 75% of the total payment records observed in the data. We conduct tests on the share of unclassified transactions and do not find any meaningful predictive power for this quantity, which supports the view that potential measurement errors in our analysis are random and not systematic.

B Proof of Propositions 1 and 2

This appendix provides a joint proof for the results stated in Propositions 1 and 2. Recall that a separating equilibrium requires conditions (6.5), (6.6), (6.7), and (6.8) to hold. In addition, the free-entry condition ensures that lender breaks even for both types of entrepreneurs,

$$(1-\pi_j)r_j = 1 \text{ for } j \in \{B, G\}\,,$$

which pins down the two interest rates:

$$r_{\text{cash}} = \frac{1}{1-\pi_B}\,, \tag{B.1}$$

$$r_{\text{cashless}} = \frac{1}{1-\pi_G}\,. \tag{B.2}$$

We now verify the conditions for the separating equilibrium. First, note that IR_B holds directly under the assumption of $(1-\pi_B)\theta \geq 1$. Intuitively, the technology has to be sufficiently profitable, as otherwise the market will break down.

Next, we verify IC_G and IC_B. Plugging the equilibrium interest rates (B.1) and (B.2) into both IC_G and IC_B yields

$$\frac{\pi_B-\pi_G}{\pi_B(1-\pi_G)(2q\pi_B-\pi_B-q+1)} \leq \phi n\theta \leq \frac{\pi_B-\pi_G}{(1-\pi_B)\pi_G(2q\pi_G-\pi_G-q+1)}\,,$$

which gives (6.10). It is easy to verify that

$$0 < \frac{\pi_B-\pi_G}{\pi_B(1-\pi_G)(2q\pi_B-\pi_B-q+1)} < \frac{\pi_B-\pi_G}{(1-\pi_B)\pi_G(2q\pi_G-\pi_G-q+1)}$$

when $\pi_G < \pi_B$. Thus, there must exist ϕ, n, and θ such that (6.10) holds.

In addition, it is easy to see that IR_G is automatically satisfied if IC_G is satisfied.

Finally, we need to verify that any potentially pooling contract is strictly dominated by the separating contracts. Under a pooling equilibrium, the lender's break-even condition becomes

$$(1-\bar{\pi})r^P = 1\,, \tag{B.3}$$

where r^P is the required repayment for both bad and good types under the pooling contract. Suppose a pooling equilibrium exists. The lender's problem becomes

$$\max_{r^P} \quad \bar{\pi} r^P \,,$$

$$\text{subject to } (IC_B) \quad (1-\pi_B)(\theta - r^P) \geq (1-\pi_B)(\theta - r_{\text{cash}})\,, \tag{B.4}$$

$$(IC_G) \quad (1-\pi_G)(\theta - r^P) \geq (1-\pi_G)(\theta - r_{\text{cashless}}) - \pi_G \mathrm{E}_G\left[C\right], \tag{B.5}$$

where (B.4) and (B.5) are the incentive compatibility constraints for the two types of entrepreneurs, and r_{cash} and r_{cashless} are given by (B.1) and (B.2) as the equilibrium interest rates in the separating equilibrium. Note that condition (B.4) always holds because $\bar{\pi} < \pi_B$. Conditions (B.3) and (B.5) then joinly imply that a pooling equilibrium exists if and only if

$$1 - \bar{\pi} \geq \frac{1-\pi_G}{1 + \phi n \theta \pi_G \left(1 - q - \pi_G + 2q\pi_G\right)} \,.$$

Therefore, to rule out the pooling equilibrium, we negate the above inequality:

$$1 - \bar{\pi} < \frac{1-\pi_G}{1 + \phi n \theta \pi_G \left(1 - q - \pi_G + 2q\pi_G\right)} \,,$$

which gives (6.11). The comparative statics immediately follow from (B.1) and (B.2), concluding the proof. □

C Alternative Specification of Information Structure

In this appendix, we provide an alternative specification of the information structure underlying the cashless payment technology. This alternative information structure is slightly more restrictive than the one used in our baseline model while allowing for the relaxiation of the assumption on the prior $\frac{1}{2} \leq \pi_G$. However, both specifications are consistent with the empirical context in India that FinTech lending promotes financial inclusion by serving subprime borrowers with a relatively low prior of success.

To that end, recall that the baseline model requires $\frac{1}{2} \leq \pi_G$ and follows Parlour, Rajan, and Zhu (2022) in specifying the information structure underlying the cashless payment technology:

$$
\begin{aligned}
&\Pr(x_i = \theta | y_i = \theta) = \Pr(x_i = 0 | y_i = 0) = q \qquad \text{and} \\
&\Pr(x_i = 0 | y_i = \theta) = \Pr(x_i = \theta | y_i = 0) = 1 - q\,.
\end{aligned}
$$

Alternatively, we can follow the idea in He, Huang, and Zhou (2023) in specifying the information structure underlying the cashless payment technology as follows:

$$
\begin{aligned}
&\Pr(x_i = \theta | y_i = \theta) = 1\,, \Pr(x_i = 0 | y_i = 0) = q \qquad \text{and} \\
&\Pr(x_i = 0 | y_i = \theta) = 0\,, \Pr(x_i = \theta | y_i = 0) = 1 - q\,.
\end{aligned}
\tag{C.6}
$$

Intuitively, this asymmetric information structure allows a good production outcome $y_i = \theta$ to be always perfectly revealed, while a bad production outcome $y_i = 0$ is accurately revealed with probability q. When the informational quality of this technology is higher, that is, when q is higher, a bad production outcome can be more accurately revealed, while the accuracy of the good production outcome is not affected. This alternative specification, as suggested by He, Huang, and Zhou (2023), is consistent with the idea of FinTech lenders developing lending technologies that allow them to better detect subprime borrowers and relatively bad production outcomes.

Under this alternative, asymmetric information structure, simple calculation can show that the expected cost of using cashless payments becomes

$$
\mathrm{E}_j\left[C\right] = \phi n \theta q \pi_j\,, \tag{C.7}
$$

which always increases in q for any $\pi_j > 0$. In addition, comparing (C.7) to (6.9), we also have $\mathrm{E}_j\left[C\right]$ increasing in ϕ, n, θ, and q, which are also held under the baseline information structure specification (6.1). Thus, repeating the derivation in Appendix B, we confirm that Propositions 1 and 2 still hold for any $\pi_j > 0$ under the alternative information structure specification (C.6).

D Cashless Payments and Willful Defaulters

In this appendix, we present three legal cases of willful defaults with a focus on how their fund diversions and other fraudulent activities were detected from cashless payment records. These cases involve detailed examinations of a company's financial records and payment history. Investigators analyze the payment records across accounts to identify any suspicious activity. These investigations often uncover discrepancies and fraudulent practices through the analysis of cashless payment records, transaction histories, and financial statements. Tracing the actual use of borrowed funds versus the declared purpose also helps identify diversion of funds. These three legal cases have two takeaways to support the modeling approach and empirical findings in our paper. Consistent with the model in Section 6, more observed discrepancies in cashless payment records lead to a higher chance of fund diversions and fraudulent activities being identified in court, which in turn implies higher monetary or reputational costs borne by the defaulter. These cases also support our empirical findings in Section 4.1 that cashless payment outflows may help detect and in turn discipline fund diversions. In the last subsection of this appendix, we also briefly discuss the prevalence of small-scale willful defaulters and the relevance of cashless payments in identifying them.

D.1 Kingfisher Airlines

One of the most famous cases of willful defaulters involves Kingfisher Airlines and its former owner, Vijay Mallya. The airline defaulted on loans worth approximately ₹9,000 crores (approximately $1.1 billion USD) from a consortium of banks. The RBI categorized Mallya as a willful defaulter, arguing that he had the means to repay the loans but deliberately chose not to. Mallya fled to the UK in 2016, leading to multiple legal battles, including extradition proceedings. The case drew widespread media attention and highlighted the issue of willful defaulters in India.[33] The accurate detection of fraudulent activities by Kingfisher Airlines and Vijay Mallya largely hinged on increasing capacity of using cashless payment records to identify diversion and misuse of loan funds. According to the RBI, payments were traced to unrelated entities, including those outside India, which had no legitimate business transactions with Kingfisher Airlines. Investigators found that loans taken for Kingfisher Airlines were diverted to other entities owned by Vijay Mallya, such as Kingfisher Finvest, an investment company that is unrelated to Kingfisher Airlines' core

[33] Details of the Kingfisher Airlines case can be found in the legal documents https://www.livelaw.in/pdf_upload/pdf_upload-373427.pdf and https://www.judiciary.uk/wp-content/uploads/2020/04/09-04-2020-State-Bank-of-India-and-Ors-v-Dr-Mallya.pdf.

business, which is consistent with our model and empirical findings that cashless payment outflows are informative about fund diversion. The funds were also allegedly used for personal purposes rather than for the intended operational needs of the airline.

D.2 Mehul Choksi and Nirav Modi

Mehul Choksi and his nephew Nirav Modi were involved in a massive fraud at Punjab National Bank (PNB), amounting to over ₹15,000 crores (approximately $1.8 billion USD). Both were declared willful defaulters by the RBI after they fled India. The case led to a major investigation and legal action by Indian authorities, including extradition requests. It also led to stricter regulatory measures against willful defaulters.[34] The fraud was uncovered when PNB officials found that unauthorized letters of undertaking (LoUs)[35] were issued to foreign banks on behalf of Nirav Modi and Mehul Choksi's firms without proper collateral. In particular, the SWIFT (Society for Worldwide Interbank Financial Telecommunication) payment system was used to communicate with overseas banks, initially bypassing the PNB's core banking system. When these payment records in SWIFT were found, it became clear that the repayment records for these LoUs were missing, leading to the discovery of the fraudulent activity. Subsequent investigations revealed that funds were siphoned off to overseas entities controlled by Modi and Choksi. SWIFT payment records also showed a pattern of using LoUs to repay previous ones, effectively rolling over the credit without actual payment.

D.3 Bhushan Steel

Bhushan Steel, one of the largest steel manufacturers in India, was declared a willful defaulter after defaulting on loans worth over ₹44,000 crores (approximately $5.3 billion USD). The case led to insolvency proceedings under the Insolvency and Bankruptcy Code (IBC), and the company was eventually taken over by Tata Steel.[36] The forensic audit of Bhushan Steel's accounts revealed numerous suspicious cashless payment records, including large

[34] Details of the Mehul Choksi and Nirav Modi case can be found at https://hbsp.harvard.edu/product/W19069-PDF-ENG.

[35] A letter of undertaking is a type of guarantee issued by an Indian bank to a foreign bank on behalf of a domestic importer. It essentially assures the foreign bank that the issuing bank (in this case, PNB) will meet the importer's payment obligations for goods or services purchased abroad.

[36] Details of the Bhushan Steel case can be found in the following legal documents: https://www.livelaw.in/pdf_upload/bhushan-steel--426382.pdf.

payments to shell companies and diversion of funds for purposes other than the stated use. In addition, the company booked fictitious sales to show inflated revenue, which helped them secure more loans. The cashless payment records and reconciliation statements revealed large inconsistencies.

D.4 Small Willful Defaulters

Similar to the high-profile legal cases involving the identification of willful defaulters mentioned earlier, cashless payments can also be helpful in identifying and classifying smaller businesses as willful defaulters, even if these cases are less likely to receive public attention. The list of willful defaulters in India is made public and can be accessed at https://www.watchoutinvestors.com/wilful_defaulters.asp. The list reveals that some defaulting amounts are as small as ₹0.01 crore (approximately $1,200 USD), with 46% of willful defaulters having defaulted on amounts of less than ₹1 crore, indicating the prevalence of small-scale willful defaulters. Additionally, banks maintain public lists of willful defaulters with details including the reasons leading to the classification of willful default, suggesting that discrepancies found in payment records are a common factor in identifying willful defaulters.[37]

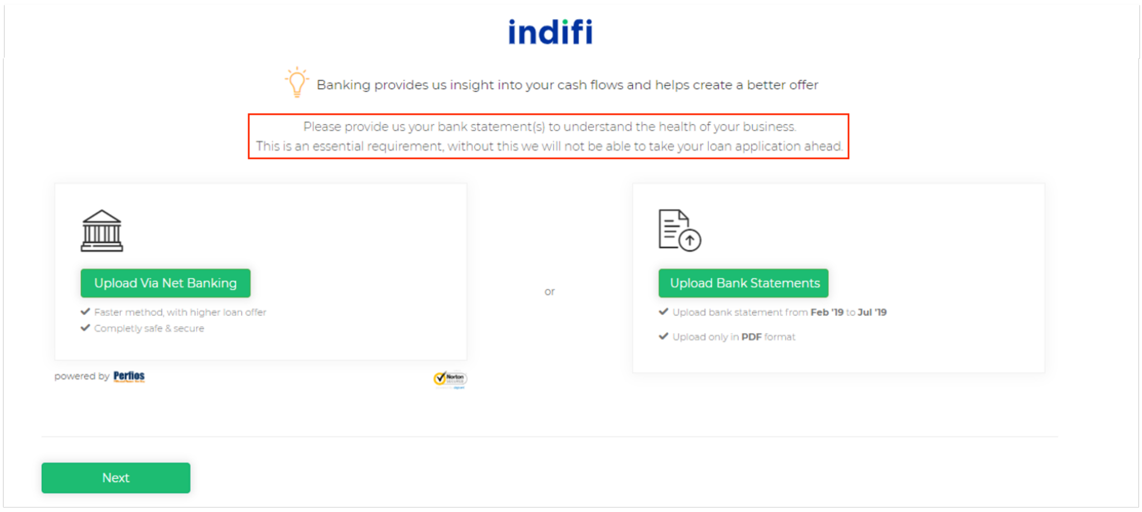
[37] For example, the IDBI bank, one of the top-10 banks in India, keeps up-to-date public lists of willful defaulters with descriptions at https://www.idbibank.in/pdf/WillfulDefaulters.xlsx.

Internet Appendix for
FinTech Lending and Cashless Payments

Pulak Ghosh   Boris Vallee   Yao Zeng

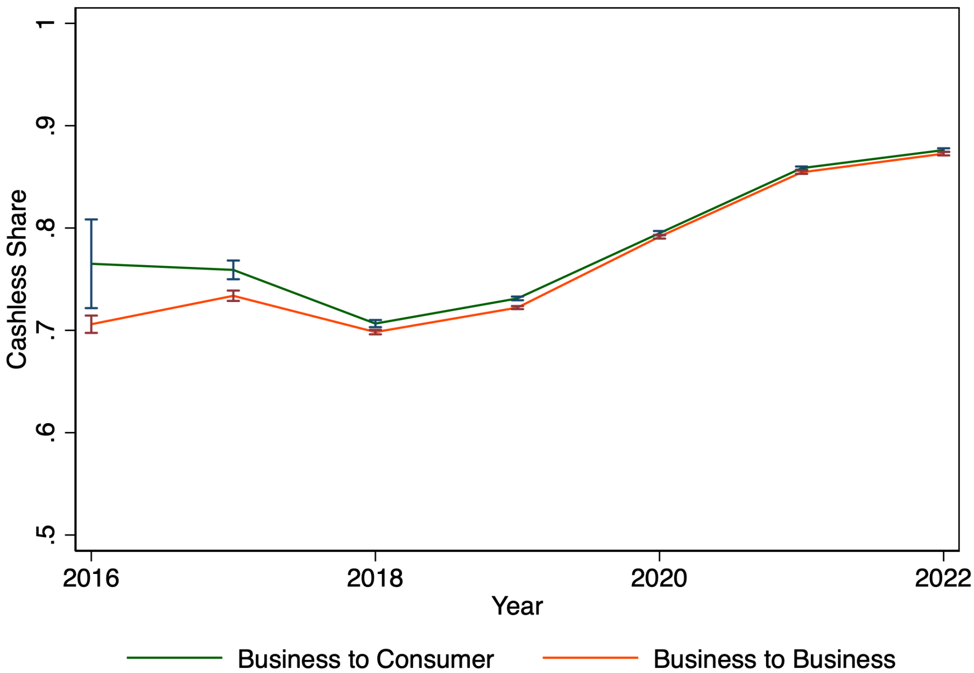
A Additional Figures and Tables

Figure A1: **Indifi: Application platform**



This figure shows the webpage that Indifi requires loan applicants to use to submit bank statements. Loan applicants can submit bank statements by either linking the bank account or by directly uploading bank statements in pdf forms.

Figure A2: **Cashless payment share evolution: B2C vs. B2B**



This figure plots the average share of cashless payments at a yearly frequency for applications from 2015-2022, splitting business-to-consumer (B2C) firms from business-to-business (B2B). Due to small sample size, the data from 2015 and 2016 are treated as a single year. B2C and B2B variables are manually coded from the industry description. The 95% confidence intervals are shown for each yearly average.

Table A1: **Cashless Payments Use by Industry**

	Obs	**Mean**	**p10**	**p25**	**p75**	**p90**
Information Technology	2341	0.930	0.800	0.904	0.999	1.000
Media & Advertising	1766	0.891	0.709	0.847	0.989	1.000
Transportation, Courier & Logistics	2911	0.889	0.714	0.845	0.981	0.998
Metals & Mining	2753	0.886	0.690	0.835	0.987	1.000
Machinery & Equipments	6662	0.879	0.688	0.827	0.980	0.999
Wood and Wood Products	825	0.875	0.692	0.828	0.973	0.998
Home furniture, Furnishings & Handicrafts	3983	0.874	0.688	0.811	0.979	1.000
Construction & Engineering	1728	0.873	0.690	0.823	0.977	0.999
Leather & Leather Products	1604	0.870	0.669	0.806	0.975	0.999
Automobile	3489	0.863	0.671	0.803	0.969	0.997
Consumer Durables, Electronics and Mobile	10412	0.862	0.668	0.792	0.975	0.999
Construction Materials	1846	0.860	0.657	0.788	0.970	0.996
Healthcare	3000	0.859	0.648	0.790	0.978	1.000
Textiles & Readymade Garment	21331	0.849	0.629	0.779	0.969	0.997
Salon & Parlour and Gym	660	0.835	0.583	0.781	0.970	1.000
Chemical and Chemical Products	1850	0.830	0.592	0.733	0.963	0.996
Travel Agency & Tour Operators	1486	0.830	0.615	0.745	0.953	0.992
Restaurant	56469	0.823	0.593	0.739	0.952	0.992
Gems & Jewellery	1847	0.823	0.573	0.728	0.966	0.999
Retail	4332	0.823	0.592	0.734	0.959	0.994
Services	11862	0.818	0.554	0.722	0.965	0.996
Hotels	1310	0.810	0.571	0.715	0.949	0.988
Agriculture & Food Products	3073	0.810	0.546	0.704	0.965	0.995
Pharmaceuticals	5263	0.797	0.543	0.702	0.945	0.989
E-Commerce	3360	0.796	0.536	0.695	0.952	0.994
ITES/ Call Centers	1374	0.790	0.514	0.682	0.955	0.996
Metal & Mining	2010	0.772	0.472	0.653	0.946	0.989

This table reports the share of cashless payments by the industry, as reported in the application process, sorted by decreasing mean. The selected industries represent the most frequent ones in our bank statement data, and they represent 90% of the observations excluding unclassified data (i.e., industries labeled as "NA" or "others").

Table A2: **Cashless Payments and Financing Outcomes: Sample Split on B2C vs. B2B**

Panel A: Business to Consumer

	(1) Approved Loan (1/0)	(2) Offered Interest Rate	(3) Amount (Log)	(4) Default
Share of cashless payments	0.018***	-0.436***	0.105***	-0.019***
	(0.001)	(0.031)	(0.007)	(0.004)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	124,201	33,676	33,674	21,758
R^2	0.192	0.200	0.307	0.158

Panel B: Business to Business

	(1) Approved Loan (1/0)	(2) Offered Interest Rate	(3) Amount (Log)	(4) Default
Share of cashless payments	0.015***	-0.441***	0.159***	-0.025***
	(0.001)	(0.030)	(0.008)	(0.004)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	187,717	32,224	32,223	19,400
R^2	0.236	0.378	0.403	0.162

This table regresses an indicator for having a loan application approved (column (1)), the loan interest rate offered (column (2)), the loan amount (column (3)), and default (column (4)) on the share of cashless payments. Panel A is restricted to Business to Consumer and Panel B is restricted to Business to Business. All variables, borrower controls, and fixed effects are constructed as specified in Table 2 and Table 3. Standard errors are clustered at the application-month level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A3: **Cashless Payments and Financing Outcomes: Industry-Year Fixed Effects**

	(1) Approved Loans	(2) Offered interest rates	(3) Amount (Log)	(4) Default
Share of cashless payments	0.015***	-0.417***	0.135***	-0.023***
	(0.002)	(0.026)	(0.008)	(0.003)
Borrower controls	Yes	Yes	Yes	Yes
Industry x Application Year FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	277,347	62,427	62,424	39,094
R^2	0.214	0.269	0.344	0.157

This table regresses an indicator for having a loan application approved (column (1)), the loan interest rate offered (column (2)), the loan amount (column (3)), and default (column (4)) on the share of cashless payments. Borrower controls and fixed effects are the same as in Table 2, with the additional introduction of industry-application year fixed effects. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A4: **Cashless Payments and Financing Outcomes: By Sub-Periods**

	(1) Approved Loan (1/0)	(2) Offered Interest Rate	(3) Amount (Log)	(4) Default
Panel A: 2015-2016				
Share of cashless payments	0.012	-0.463***	0.207***	-0.013
	(0.010)	(0.057)	(0.048)	(0.017)
Observations	1,699	1,044	1,044	668
R^2	0.322	0.475	0.434	0.275
Panel B: 2017-2018				
Share of cashless payments	0.011***	-0.402***	0.183***	-0.031***
	(0.002)	(0.038)	(0.012)	(0.007)
Observations	48,592	12,893	12,893	8,469
R^2	0.341	0.518	0.376	0.168
Panel C: 2019-2020				
Share of cashless payments	0.013***	-0.367***	0.107***	-0.026***
	(0.001)	(0.028)	(0.006)	(0.003)
Observations	157,576	29,589	29,589	17,972
R^2	0.236	0.261	0.276	0.101
Panel D: 2021-2022				
Share of cashless payments	0.022***	-0.633***	0.121***	0.002
	(0.002)	(0.039)	(0.008)	(0.002)
Observations	103,935	22,249	22,246	13,942
R^2	0.141	0.184	0.222	0.068
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes

This table presents regressions similar to the main results seen in Table 2. However, each panel displays the regressions when restricted to a two-year period. Panel A displays regressions for the years 2015 to 2016, Panel for 2017 to 2018, Panel C for 2019 to 2020, and Panel D for 2021 to 2022. All variables, borrower controls, and fixed effects are constructed as specified in Table 2. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A5: **Cashless Payments and Financing Outcomes: Gradual Fixed Effects**

Panel A: Approved Loan (1/0)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of cashless payments	0.041***	0.011***	0.007***	0.020***	0.017***	0.015***	0.017***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Borrower controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
Application month FE	No	No	No	Yes	Yes	Yes	Yes
Cibil score group FE	No	No	No	No	Yes	Yes	Yes
3-digit zipcode FE	No	No	No	No	No	Yes	Yes
Revenue deciles FE	No	No	No	No	No	No	Yes
Observations	316,407	314,537	314,537	314,537	314,536	311,941	311,941
R^2	0.010	0.100	0.142	0.168	0.205	0.212	0.218

Panel B: Interest Rate Offered

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of cashless payments	-0.469***	-0.350***	-0.422***	-0.493***	-0.465***	-0.436***	-0.441***
	(0.042)	(0.041)	(0.026)	(0.024)	(0.023)	(0.024)	(0.024)
Borrower controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
Application month FE	No	No	No	Yes	Yes	Yes	Yes
Cibil score group FE	No	No	No	No	Yes	Yes	Yes
3-digit zipcode FE	No	No	No	No	No	Yes	Yes
Revenue deciles FE	No	No	No	No	No	No	Yes
Observations	66,010	65,985	65,985	65,984	65,982	65,942	65,942
R^2	0.010	0.132	0.209	0.246	0.263	0.280	0.281

Panel C: Amount (Log)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of cashless payments	0.287***	0.244***	0.197***	0.143***	0.138***	0.136***	0.134***
	(0.016)	(0.015)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Borrower controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
Application month FE	No	No	No	Yes	Yes	Yes	Yes
Cibil score group FE	No	No	No	No	Yes	Yes	Yes
3-digit zipcode FE	No	No	No	No	No	Yes	Yes
Revenue deciles FE	No	No	No	No	No	No	Yes
Observations	66,006	65,981	65,981	65,980	65,978	65,938	65,938
R^2	0.070	0.191	0.268	0.322	0.335	0.345	0.349

Panel D: Default (1/0)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of cashless payments	-0.002**	-0.031***	-0.026***	-0.017***	-0.016***	-0.017***	-0.018***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Borrower controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
Application month FE	No	No	No	Yes	Yes	Yes	Yes
Cibil score group FE	No	No	No	No	Yes	Yes	Yes
3-digit zipcode FE	No	No	No	No	No	Yes	Yes
Revenue deciles FE	No	No	No	No	No	No	Yes
Observations	316,407	65,981	65,981	65,980	65,978	65,938	65,938
R^2	0.000	0.026	0.042	0.073	0.077	0.083	0.090

This table presents regression coefficients similar to the ones in Table 2, but with gradual introduction of fixed effects. Panel A regresses on an indicator for having its loan application approved on the share of cashless payments with increasing levels of fixed effects. Panel B does the same with an indicator for the interest rate offered, Panel C for the log amount of the loan, and Panel D for an indicator for loan default. All variables, borrower controls, and fixed effects are constructed as specified in Table 2. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A6: **Cashless Payments and Financing Outcomes: Robustness to Standard Error Clustering**

Panel A: Approved Loans

	(1)	(2)	(3)	(4)	(5)
Share of cashless payments	0.017***	0.017***	0.017***	0.017***	0.017***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)
Application Month Cluster	Yes	No	No	Yes	Yes
Industry Cluster	No	Yes	No	Yes	Yes
3-Digit Zipcode Cluster	No	No	Yes	No	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes	Yes
3-digit Zipcode FE	Yes	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes	Yes
Observations	311,941	311,941	311,941	311,941	311,941
R^2	0.218	0.218	0.218	0.218	0.218

Panel B: Interest Rate Offered

	(1)	(2)	(3)	(4)	(5)
Share of cashless payments	-0.441***	-0.441***	-0.441***	-0.441***	-0.441***
	(0.024)	(0.030)	(0.030)	(0.034)	(0.040)
Application Month Cluster	Yes	No	No	Yes	Yes
Industry Cluster	No	Yes	No	Yes	Yes
3-Digit Zipcode Cluster	No	No	Yes	No	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes	Yes
3-digit Zipcode FE	Yes	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes	Yes
Observations	65,942	65,942	65,942	65,942	65,942
R^2	0.281	0.281	0.281	0.281	0.281

Panel C: Amount (Log)

	(1)	(2)	(3)	(4)	(5)
Share of cashless payments	0.134***	0.134***	0.134***	0.134***	0.134***
	(0.006)	(0.014)	(0.010)	(0.015)	(0.017)
Application Month Cluster	Yes	No	No	Yes	Yes
Industry Cluster	No	Yes	No	Yes	Yes
3-Digit Zipcode Cluster	No	No	Yes	No	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes	Yes
3-digit Zipcode FE	Yes	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes	Yes
Observations	65,938	65,938	65,938	65,938	65,938
R^2	0.349	0.349	0.349	0.349	0.349

Panel D: Defaults

	(1)	(2)	(3)	(4)	(5)
Share of cashless payments	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Application Month Cluster	Yes	No	No	Yes	Yes
Industry Cluster	No	Yes	No	Yes	Yes
3-Digit Zipcode Cluster	No	No	Yes	No	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes	Yes
3-digit Zipcode FE	Yes	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes	Yes
Observations	65,938	65,938	65,938	65,938	65,938
R^2	0.090	0.090	0.090	0.090	0.090

This table presents regression coefficients similar to the main results seen in Table 2, but with different levels of clustering. Panel A regresses on an indicator for having its loan application approved on share of cashless payments, Panel B does the same with an indicator for interest rate offered, Panel C for the log amount of the loan, and Panel D for an indicator of loan defaults. All variables, borrower controls, and fixed effects are constructed as specified in Table 2. Standard errors are displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A7: **Cashless Payments and Financing Outcomes: Sample Split on Having a Credit Score**

Panel A: No Cibil Score

	(1) Approved Loan (1/0)	(2) Offered Interest Rate	(3) Amount (Log)	(4) Default
Share of cashless payments	0.008***	-0.478***	0.140***	-0.023**
	(0.002)	(0.077)	(0.017)	(0.011)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	34,545	3,395	3,395	1,998
R^2	0.224	0.495	0.456	0.265

Panel B: Has Cibil Score

	(1) Approved Loan (1/0)	(2) Offered Interest Rate	(3) Amount (Log)	(4) Default
Share of cashless payments	0.018***	-0.437***	0.133***	-0.022***
	(0.001)	(0.024)	(0.006)	(0.003)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	277,369	62,464	62,461	39,138
R^2	0.216	0.270	0.344	0.152

This table regresses an indicator for having a loan application approved (column (1)), the loan interest rate offered (column (2)), the loan amount (column (3)), and default (column (4)) on the share of cashless payments. Panel A is restricted to applicants that have no Cibil score, the Indian credit score. Panel B is restricted to applicants that have a Cibil score. All variables, borrower controls, and fixed effects are constructed as specified in Table 2 and Table 3. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A8: **Cashless Payments and Financing Outcomes: Dropping Large Firms**

	(1) Approved Loans	(2) Offered interest rates	(3) Amount (Log)	(4) Default
Share of cashless payments	0.017***	-0.403***	0.118***	-0.023***
	(0.001)	(0.024)	(0.005)	(0.003)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	279,788	57,067	57,064	34,909
R^2	0.221	0.283	0.332	0.154

This table presents regression coefficients similar to the main results seen in Table 2, but with firms from the top decile of revenues removed from the sample. All variables, borrower controls, and fixed effects are constructed as specified in Table 2. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A9: **Cashless payments and Take Up**

	Take Up	
	(1)	(2)
Share of cashless payments	-0.019***	-0.019***
	(0.003)	(0.003)
Borrower controls	Yes	Yes
Industry FE	Yes	Yes
Application month FE	Yes	Yes
Cibil score group FE	No	Yes
3-digit zipcode FE	No	Yes
Revenue deciles FE	No	Yes
Observations	65,983	65,941
R^2	0.065	0.078

This table presents regression coefficients that regress an indicator for the loan offer being taken up on the share of cashless payments. All variables, borrower controls, and fixed effects are constructed as specified in previous tables. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A10: **Complementarity With Other Signals: Inflow Volatility**

	Approved loan (1/0) (1)	Offered interest rate (2)	log (Amount) (3)	Default (4)
Share of cashless payments	0.018***	-0.401***	0.126***	-0.001***
	(0.001)	(0.023)	(0.006)	(0.000)
Weekly inflow volatility	-0.014***	0.194***	-0.104***	0.000
	(0.003)	(0.044)	(0.010)	(0.000)
Share of cashless payments × Weekly inflow volatility	-0.003***	0.207***	-0.038***	0.002***
	(0.001)	(0.023)	(0.005)	(0.000)
Borrower controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Application month FE	Yes	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes	Yes
3-digit zipcode FE	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Observations	311,938	65,942	65,938	311,938
R^2	0.218	0.282	0.351	0.035

This table presents regression coefficients similar to Panel B from Table 7, but using weekly inflow volatility instead of weekly outflow. Weekly inflow volatility is defined as weekly revenue over monthly spending. This term is both standardized and winsorized. All variables, borrower controls, and fixed effects are constructed as specified in Table 7. Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A11: **Balance of Applicant Characteristics: Banking at a Currency Chest (0/1)**

	Without currency chest branch			**With currency chest branch**		
	Obs	**Mean**	**SD**	**Obs**	**Mean**	**SD**
				Panel A. Loan Applicant Characteristics		
Year of Application	305,189	2020	1.4	11,530	2020	1.4
Applicant Age	303,469	36.6	9.3	11,421	36.4	9.5
Business Age	305,189	4.3	4.5	11,530	4.8	5.3
Cibil Score	305,189	613	247.4	11,530	592	266.7
Credit History Length (in Years)	271,896	7.8	5.8	10,070	7.5	5.7
				Panel B. Banking Statement Data		
Share of Cashless Payments	304,892	0.780	0.2	11,515	0.747	0.2
of which: Information-intensive Payments	304,892	0.528	0.3	11,515	0.525	0.3
Share of Cash Payments	304,892	0.220	0.2	11,515	0.253	0.2
Avg. Monthly Revenue (INR in thousand)	305,189	1384	9092.0	11,530	1243	7212.6
Avg. # of Transactions	305,189	740	1474.1	11,530	687	1320.7

This table reports the characteristics for applicant firms that bank at currency chest branches versus those that bank at other branches. Panel A compares applicants' characteristics by application year, age, credit score, and credit history. Panel B compares banking statements of applicants by payment technology, bank type, and monthly average revenue.

Table A12: **IV: Sample Split on B2C vs. B2B**

Panel A: Business to Consumer (B2C)

	Share of cashless payments		Approved Loan (1/0)		
	(1)	(2)	(3)	(4)	(5)
$\widehat{\text{Share of cashless payments}}$			0.245	0.206	0.361
			(0.155)	(0.250)	(0.303)
$\widehat{\text{Share of cashless payments}}$ × Cibil Score					0.192
					(0.172)
Chest in 2018 or 2019	-0.092***	-0.059**			
	(0.031)	(0.029)			
Borrower banks at Chest Bank (1/0)	-0.035**	0.021	-0.024*	-0.017**	-0.016*
	(0.015)	(0.016)	(0.014)	(0.007)	(0.009)
Year FE	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Application month FE	No	Yes	No	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	Yes
3-digit zipcode FE	No	Yes	No	Yes	Yes
Revenue deciles FE	No	Yes	No	Yes	Yes
Observations	125,109	124,201	125,109	124,201	111,647
F-statistic	8.75	3.36	-	-	-

Panel B: Business to Business (B2B)

	Share of cashless payments		Approved Loan (1/0)		
	(1)	(2)	(3)	(4)	(5)
Share of cashless payments			0.105*	0.116*	0.110*
			(0.063)	(0.062)	(0.061)
Share of cashless payments × Cibil Score					0.032***
					(0.009)
Chest in 2018 or 2019	-0.135***	-0.128***			
	(0.025)	(0.026)			
Borrower banks at Chest Bank (1/0)	-0.050***	0.009	-0.010	-0.002	-0.000
	(0.017)	(0.019)	(0.009)	(0.006)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Application month FE	No	Yes	No	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	Yes
3-digit zipcode FE	No	Yes	No	Yes	Yes
Revenue deciles FE	No	Yes	No	Yes	Yes
Observations	191,298	187,717	191,298	187,717	164,214
F-statistic	33.09	23.41	-	-	-

This table presents regression coefficients for a 2SLS specification similar to Table 8. Panel A is restricted to Business to Consumer and Panel B is restricted to Business to Business. All variables, borrower controls, and fixed effects are constructed as specified in Table 8. The reported F-statistic is the 'Effective F-Stat' as described in Montiel Olea and Pflueger (2013). Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A13: **IV: Cashless Payment Use and Loan Approval without Time Interaction**

	(1) Share of cashless payments	(2) Share of cashless payments	(3) Approved Loan (1/0)	(4) Approved Loan (1/0)	(5) Approved Loan (1/0)
$\widehat{\text{Share of cashless payments}}$			0.286***	0.311***	0.279***
			(0.042)	(0.105)	(0.102)
$\widehat{\text{Share of cashless payments}}$ × Cibil Score					0.063***
					(0.012)
Borrower banks at Chest Bank (1/0)	-0.110***	-0.044***			
	(0.014)	(0.012)			
Year FE	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Application month FE	No	Yes	No	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	Yes
3-digit zipcode FE	No	Yes	No	Yes	Yes
Revenue deciles FE	No	Yes	No	Yes	Yes
Observations	314,756	310,425	314,756	310,425	276,117
F-statistic	65.91	11.87	-	-	-

This table presents regression coefficients for a 2SLS specification for the time period after Demonetization. We present the first-stage coefficients in columns (1) and (2), where we regress the share of cashless payments on the instrument defined as the interaction between an indicator variable for banking at a currency chest branch. Column (1) only controls for an indicator variable for banking at a currency chest branch, as well as yearly fixed effects. Column (2) runs the same analysis with additional fixed effects. The second stage of our analysis is presented in columns (3) to (5), where we regress an indicator variable for the application being approved on the instrumented share of cashless payments. Column (3) controls for for an indicator variable for banking at a currency chest branch, as well as yearly fixed effects. Column (4)runs the same analysis with additional fixed effects. Column (5) additionally interacts the instrumented share of cashless payments with the applicant's Cibil score, keeping the same comprehensive fixed effects. The share of cashless payments is calculated as per Section 2.2 and is then standardized. The set of borrower controls includes the log number of payment records, credit history length, business vintage, the log of owner's age, missing credit score indicator, and top-up loan indicator. There are 67 industries. Cibil score groups represent 10-point bands of the Cibil score, the Indian equivalent of the FICO score. Revenues are calculated as the sum of inflows on the bank account over the six months before the application. The reported F-statistic is the 'Effective F-Stat' as described in Montiel Olea and Pflueger (2013). Standard errors are clustered at both the industry and application year level and displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A14: **IV: 3-digit Zipcode-Year Standard Error Clustering**

	Share of cashless payments		Approved Loan (1/0)		
	(1)	(2)	(3)	(4)	(5)
Share of $\widehat{\text{cashless}}$ payments			0.190**	0.117*	0.125*
			(0.077)	(0.070)	(0.073)
Share of $\widehat{\text{cashless}}$ payments × Cibil Score					0.056***
					(0.015)
Chest in 2018 or 2019	-0.128***	-0.108***			
	(0.032)	(0.024)			
Borrower banks at Chest Bank (1/0)	-0.047**	0.013	-0.005	-0.009*	-0.007
	(0.019)	(0.015)	(0.009)	(0.005)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Application month FE	No	Yes	No	Yes	Yes
Cibil score group FE	No	Yes	No	Yes	Yes
3-digit zipcode FE	No	Yes	No	Yes	Yes
Revenue deciles FE	No	Yes	No	Yes	Yes
Observations	313,486	311,941	313,486	311,941	275,889
F-statistic	16.01	20.02	-	-	-

This table presents regression coefficients for a 2SLS specification similar to Table 8, but clustered by zipcode-year as well as application month. Zipcode-year is constructed from the unique observations of the first three digits of the Indian Pincode and the loan application year. All variables, borrower controls, and fixed effects are constructed as specified in Table 8. The reported F-statistic is the 'Effective F-Stat' as described in Montiel Olea and Pflueger (2013). Standard errors are displayed below the coefficient of interest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.