

FinTech Lending and Cashless Payments*

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Abstract

This study provides a new perspective to understand the rise and future potential of FinTech lending by linking it to the informational role of cashless payments. We uncover both theoretically and empirically a synergy between FinTech lending and cashless payments. FinTech lenders screen borrowers more efficiently when borrowers use more cashless payments that produce transferrable and verifiable information. Because borrowers expect lenders to rely on such payment information to screen them, a strategic consideration for a borrower to stand out of other borrowers then pushes more borrowers to adopt cashless payments. Using novel loan-level data from a large Indian FinTech lender who focuses on small-business lending, we find that a larger use of verifiable cashless payments (relative to cash) predicts a higher chance of loan approval, a lower interest rate, and lower default conditional on the interest rate obtained. These relationships are more pronounced for higher-quality firms. The uncovered synergy provides a plausible explanation for the joint rise of FinTech lending and cashless payments, and suggests an alternative banking model without a balance sheet or traditional banking relationships. Our findings also provide new policy implications on data sharing and open banking.

Keywords: FinTech, lending, payments, data sharing

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1 Introduction

The past decade has witnessed a drastic rise of lending by FinTech companies, which was traditionally dominated by banks.¹ It is well understood that banks' informational advantage in lending stems from their relationships with borrowers from repeated lending (e.g., [Diamond, 1991](#), [Rajan, 1992](#)) and from deposit-taking (e.g., [Berlin and Mester, 1999](#), [Puri, Rocholl, and Steffen, 2017](#)), both helping produce borrower information *inside* the same bank. Without enjoying such relationships and the resulting inside information production, how can FinTech lenders compete with banks and even become dominating in some lending markets?

In this paper, we provide a new perspective to understand the rise and future potential of FinTech lending by linking it to the informational role of another important financial service: cashless payments.² We uncover both theoretically and empirically a synergy between FinTech lending and cashless payments, the latter producing borrower information *outside* the lender. This synergy in producing outside information leads to a hand-in-hand rise of both FinTech lending and cashless payments, and also suggests an alternative banking model without a balance sheet and without relationships in the traditional sense.

Our study builds on two simple observations and yields novel predictions. First, FinTech lenders typically use outside verifiable information to assess borrowers' creditworthiness beyond the usual credit bureau inquiry. Second, cashless payment service providers collect the abundant verifiable data generated through the use of their service. Building on these two observations, we develop a theoretical framework showing that the interaction between

¹As per the Financial Stability Board (FSB) and Basel Committee, FinTech is defined as “technologically enabled financial innovation that could result in new business models, applications, process, or products with an associated material effect on financial markets and institutions, and the provision of financial services.” In the U.S., FinTech lending has been becoming dominating in some of the most important lending markets including the mortgage markets (e.g., [Buchak, Matvos, Piskorski, and Seru, 2018](#), [Fuster, Plosser, Schnabl, and Vickery, 2019](#)) and has also developed dramatically in small-business lending markets (e.g., [Gopal and Schnabl, 2020](#)). The rise of FinTech lending has also been particularly pronounced in developing economics ([Claessens, Frost, Turner, and Zhu, 2018](#)).

²The rise of cashless payments has speeded up since the global financial crisis and has coincided with the rise of FinTech, with the global revenue reaching two trillion dollars ([Vives, 2019](#)). A large share of cashless payments is operated by traditional banks. Several trends have also motivated non-bank institutions to participate, including the willingness to tackle fraud, lower operating costs, and the development of novel payment technologies.

FinTech lenders and cashless payments fosters the development of both technologies. In one direction, FinTech lenders become more efficient in screening high- versus lower-quality borrowers when borrowers adopt cashless payments that produce more verifiable information. In the other direction, because would-be borrowers expect lenders to rely on outside verifiable payment information to screen them, a strategic consideration for a borrower to stand out of worse borrowers emerges, which ultimately pushes all borrowers to adopt cashless payments. This synergy further implies that even without policies to promote data sharing or open banking such as the Second Payment Services Directive (PSD2) in Europe, borrowers may voluntarily commit to data sharing in order to improve their outcome on the lending markets.

More specifically, we build a simple model of FinTech lending and borrowers' choice of payment methods to illustrate how the synergy arises in equilibrium. In the model, there is a risk-neutral firm and a risk-averse financier, both are competitive. A firm of higher type has a better investment technology, and thus more likely to produce a product of higher quality. Only the firm is privately informed about its type. Thus, the financier relies on its prior belief and any information available to decide whether to finance the firm. Prior to this financing stage, each firm chooses their payment technology for the period preceding the loan application, which we call the production stage. Cash does not leave any verifiable information about the production outcomes. The cashless payment service, in contrast, can record and keep verifiable information about all the production outcomes and make them available for the financier's potential use in the financing stage. If the firm adopts cashless payments, it commits to provide whatever information being generated to the financier in the financing stage, consistent with the practice that FinTech lenders can easily access and use verifiable information generated by outside payment service providers. Thus, the firm optimally chooses whether to use cashless payments at the beginning under the expectation that the financier will use the information generated to make financing decisions.³

We illustrate the synergy between lending and cashless payments in two steps, each of

³To focus on the informational role of cashless payments, we abstract away from their other benefits and costs (i.e., safety or convenience yields).

which highlights one direction of the synergy. We start by showing how cashless payments improves lending outcomes by highlighting two complementary informational effects of verifiable payment records. First, when a firm adopts the verifiable cashless payment service, the payment records help reveal the quality of the firm’s technology. This information-revealing effect allows the financier to better screen the firm and achieve more efficient financing outcomes. Particularly, the information-revealing effect benefits firms of better types, and is stronger when the firm can establish more payment records or the payment records are more verifiable. Second, verifiable payment records also directly reduce the financing risk that the financier bear by reducing the variance when the financier makes inference about the firm type, and this risk-reducing effect benefits both the financier and all firm types. The overall impact of adopting cashless payments on lending outcomes thus depend on the combination of the two effects.

We then show how lending based on outside verifiable information fosters the adoption of cashless payments. The firm, expecting to be screened by the financier who can access the outside payment information, optimally adopts the the verifiable cashless payment service. This is true even if the information-revealing effect dominates and low-type firms may be hurt by revealing the quality of their technology. Although surprising at the first glance, this force stems from an intuitive strategic consideration among different firm types. When high firm types adopt cashless payments, the financier will rationally update its belief and expect any firm using cash to be of a low type. Thus, a relatively low-type firm would find it optimal to stand out from even lower-type firms by adopting cashless payments. Ultimately, all firm types adopt cashless payments.⁴ Therefore, the rise of FinTech lending and its reliance on outside verifiable payment information in turn fosters the rise of cashless payments.

To test our model predictions, we use novel loan application-level data from one of the largest Indian FinTech lenders, Indifi, which focuses on small business loans. The lending

⁴This logic resembles the “unraveling argument” first analyzed in an information disclosure context by [Milgrom \(1981\)](#). Indeed, when the financier can efficiently use outside verifiable information to screen firms, committing to generate such information by adopting cashless payments can be interpreted as an information disclosure decision for the firms.

context in India and broader emerging economics is a relevant laboratory to test our model predictions, as the joint rise of FinTech lending and cashless payments has been particularly pronounced in these economies. The data we exploit in the study is also particularly suited to our analysis as it includes borrowers' detailed payment information disaggregated at the payment level. We first develop a methodology to classify each payment appearing on bank statements into cash and cashless payments. Within cashless payments, we can further break down between information-intensive and information-light methods of payments, depending on whether payments are partly aggregated, and whether the payment counter-party is known in the statements. Being able to access such payment-level information not only allows Indifi to potentially screen the borrowers more efficiently, but also uniquely allows us as econometricians to test how payment information with varying level of verifiability affects lending outcomes. The data also includes a wealth of granular information including applicants' business characteristics as well as their credit bureau data, which allows us to precisely pinpoint the role of outside payment information vs. traditionally openly accessible data.

Equipped with this data and measures of use of cashless payments, we study whether such use correlates with loan screening outcomes on both the extensive and intensive margins, controlling non-linearly for a wealth of applicant characteristics such as business size, age, 3-digit zip code, and owner credit score. First, we find that a higher use of cashless payments (and relatively, a lower use of cash) is associated with improved borrowing outcomes: applicants relying heavily on cashless payments are more likely to obtain a loan, and when doing so obtain a lower interest rate. At the same time, we find that such borrowers also get significantly lower rate from the FinTech lender than from previous loans with traditional banks. Second, this benefit is particularly pronounced for cashless payment users that present a low level of risk, as proxied by the volatility of their revenues. These relationships appear to be more pronounced when focusing on more verifiable cashless payments, such as individual internet transfers, as opposed to less verifiable ones, such as mobile payments that aggregate payments and do not provide information about the

transacting counter-party. Finally, turning to loan default, we find that within loans charging the same interest rate, borrowers that use more cash transactions are more likely to default. This suggests that the use of cashless payments indeed helps the FinTech lender to price loans more efficiently, leading to more efficient capital allocation among different borrowers.

To gain causal identification on the impact of cashless payments on loan application outcomes, we utilize a unique institutional setting in India. We instrument the reliance on cash payments with an indicator variable for the borrower banking at a reserve chest bank, that is, a bank branch that distributes new banknotes and collect damaged old ones. Banking at such an establishment after the demonetization is indeed predictive of a higher use of cash, as chest bank clients had better access to the new banknotes during the initial shortage of cash, and therefore switched less to other means of payment. When instrumenting the use of cash with this plausibly exogenous variation, our previous result is strengthened: we find that cash use negatively impacts the likelihood of obtaining a loan, with a magnitude that is economically significant.

Taken together, our theoretical framework and empirical results provide a new perspective to understand the interaction between the rise of FinTech lenders and the development of cashless payments. In one direction, our findings of cashless payments improving lending efficiency provide direct evidence in support of policies that promote data sharing and open banking. In the other direction, the prediction of a universal adoption of verifiable payment service is consistent with the trends of many economies increasingly switching to cashless payments hand-in-hand with the rise of FinTech lending, particularly in developing economies such as China, India, or Kenya. The synergy we document also provides an economic rationale for the recent trends of FinTech lenders directly offering payment service, and payment service firms and marketplaces offering credit.⁵ Despite expanding their scope, these institutions remain fundamentally different from traditional banks as they do

⁵OnDeck started to provide payment service to their borrowers, and PayPal, Square, and Stripe all started to offer loans. Amazon and Alibaba are prominent examples of marketplaces offering loans to their partners.

not accept deposits and are not regulated as banks. These developments suggests the emergence of an alternative banking model without a balance sheet and without relationships in the traditional sense.

1.1 Related Literature

At the conceptual level, our paper contributes to the large relationship banking literature (see [Diamond \(1991\)](#) and [Rajan \(1992\)](#) for pioneer work and [Liberti and Petersen \(2019\)](#) for a modern survey about the role of information in bank lending). Specifically, a branch of this literature suggests that relationship-specific payment processing by a bank for its borrowers helps to ease information asymmetry between the two parties and facilitate lending by the *same* bank to those borrowers (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 bank balance sheet. Our paper shows that the existence of a shared bank balance sheet or relationships inside the same bank is not a necessary condition for such informational spillover between lending and payments. As long as payment information is verifiable, a stand-alone lender may rely on it to better infer about borrower’s creditworthiness, and this reliance in turn encourages borrowers to use verifiable payment service in the first place.

Our paper then contributes to the literature both on FinTech lending and cashless payments. On the lending side, several papers explore the driving forces behind the boom of FinTech lending in both consumer loans ([Buchak, Matvos, Piskorski, and Seru, 2018](#), [Fuster, Plosser, Schnabl, and Vickery, 2019](#)) and small-business loans ([Gopal and Schnabl, 2020](#)), focusing on the roles of regulatory arbitrage, convenience and screening technology.⁶ Our paper highlights a novel driver for FinTech competitiveness against traditional banks: access to verifiable payment information. In this aspect, our paper is closely related to [Berg, Burg, Gombovic, and Puri \(2020\)](#) who empirically show that “digital footprints” such as

⁶A related literature considers marketplace or peer-to-peer lending powered by FinTech platforms, which rely on end-investor screening and we do not focus on this aspect in this paper given the sophistication needed to analyze payment data. Examples include [Duarte, Siegel, and Young \(2012\)](#), [Iyer, Khwaja, Luttmer and Shue \(2015\)](#), [Balyuk \(2017\)](#), [Tang \(2019\)](#) and [Vallee and Zeng \(2019\)](#).

website registration can predict consumer defaults and thus improve lending outcomes. Complementing theirs, we focus on payment information, which may be at least partly generated by borrowers through their choice of technology to be provided for future loan application. This difference allows us to pinpoint why such information causally matters for lending outcomes both theoretically and empirically, and how such impact results in both increased adoption of cashless payments and voluntary provision of such information by borrowers.

On the payment side, the literature mainly focuses on direct benefits of cashless payments and the impacts on their adoption (e.g. [Agarwal, Basu, Ghosh, Pareek, and Zhang, 2018](#), [Higgins, 2019](#), [Chodorow-Reich, Gopinath, Mishra, and Narayanan, 2020](#), [Crouzet, Gupta, and Mezzanotti, 2020](#)). Our work more closely complements [Parlour, Rajan, and Zhu \(2020\)](#) who theoretically study the competition between FinTech payments and traditional banks providing both lending and payment service and who also focus on their informational role. We differ by focusing on the interaction between FinTech lending and cashless payments.⁷ The endogenous and joint rise of both technologies illustrated by our framework thus provides a different angle to understand why FinTech players may successfully compete with traditional banks.

Given the focus on the informational roles of payments, our paper also contributes to a burgeoning literature on the data market and the incentives of data sharing (see [Bergemann and Bonatti, 2019](#), for a survey). Closely related is [He, Huang, and Zhou \(2020\)](#) who also focus on lending and theoretically examine the competition between traditional banks and FinTech lenders when borrowers share their bank data with FinTech lenders. While our empirical evidence is consistent with their model’s prediction that sharing bank statements that contain payment information improves lending outcomes from FinTech lenders, we differ theoretically from this study by considering the strategic interaction in data sharing. The need to stand out from other borrowers pushes every borrower to share data, which

⁷An important modeling difference is that the borrower in our model is privately informed about its technology (i.e., quality), while in their model both the lenders and the borrowers are uninformed about borrowers’ credit quality ex-ante. The information asymmetry between the lender and borrowers allows us to study borrowers of what quality will optimally adopt verifiable payment service in equilibrium.

is critical in the synergy between FinTech lending and cashless payments. Our unraveling mechanism in the spirit of [Milgrom \(1981\)](#) also complements the idea of data externality in the recent literature that an agent’s data sharing creates an externality on other agents because one’s data is revelatory of others’ (e.g., [Acemoglu, Makhdoumi, Malekian, and Ozdaglar, 2018](#), [Bergemann, Bonatti, and Gan, 2020](#), [Liu, Sockin, and Xiong, 2020](#)).

The remaining of the paper is as follows. [Section 2](#) presents our theoretical framework. [Section 3](#) describes the data and institutional details. [Section 4](#) presents the empirical analysis. [Section 5](#) concludes.

2 Theoretical Framework

2.1 Setting

We build a simple model to capture the interaction of payments and lending outcomes while highlighting the informational channels between the two. The model has two representative agents: a competitive risk-neutral firm and a competitive risk-averse financier. Time is discrete: $t = 0, 1, 2, \dots, n, n + 1$ with $n \geq 1$. We call $\{0, \dots, n - 1\}$ the production stage and n the lending stage. The firm has a risky technology, the quality of which is characterized by $z \in \bar{\mathbb{R}}$, the extended real set. Only the firm is privately informed about z , and thus we call z the firm’s type, and the financier’s prior follows a normal distribution $z \sim N(\mu, \tau_z^{-1})$. If the technology is operated at t , it can produce a product of quality y_t to be delivered at $t + 1$, and the product quality is also i.i.d. normally distributed given the quality of technology: $y_t \sim N(z, \tau_y^{-1})$. Intuitively, a better technology is more likely to produce a better product. The firm has enough capital to operate the technology in the production stage, that is, during $t \in \{0, \dots, n - 1\}$, yielding a series of realized production outcomes $Y = \{y_t | 0 \leq t \leq n - 1\}$.

At the beginning of the production stage $t = 0$, the firm chooses how to accept payments for the products produced. It can either accept payments in cash, which renders the production outcomes Y non-verifiable, or it can commit to using an outside cashless payment service that allows the realized production outcomes to be documented as a file

of payment records, which is verifiable and can be accessed by the financier in the lending stage. For each production outcome y_t , the cashless payment service can generate a record $x_t \sim N(y_t, \tau_x^{-1})$, where the precision τ_x can be naturally interpreted as the level of verifiability. The higher the precision τ_x is, the more verifiable the payment record is. The file of all verifiable payment records can be then denoted by $X = \{x_t | 0 \leq t \leq n - 1\}$.

REMARKS. To focus on the informational role of cashless payments compared to cash, we do not consider either the convenience yields or the physical costs of using different types of payment methods. The binary choice between cash and one single verifiable cashless payment service over the entire production period is a parsimonious way to capture the essence of payment technology choice. In reality, a firm may mix a spectrum of payment methods with different degrees of verifiability.⁸ We also note that the length of the production period does not correspond to the firm's life cycle but rather to how many verifiable payment records the firm may potentially establish.⁹

At the financing stage $t = n$, the firm does not have capital any more to operate the technology, and thus has to finance the technology through the financier. We assume that the financier has a CARA utility function with absolute risk aversion ρ . Modeling FinTech lenders as being risk-averse allows us to parsimoniously capture the various financial constraints that they face, which effectively make them risk-averse. Importantly, the financier does not know the quality of the firm's technology, and thus must infer it based on the prior and the payment records X that the firm submits, if any. Under the CARA-normal framework, the financier effectively has a mean-variance utility, and thus the effective financing price bid by the competitive financier is

$$p = E[y_n | \mathcal{I}_n] - \frac{\rho}{2} Var[y_n | \mathcal{I}_n],$$

⁸For example, checks are more verifiable than cash but less than online banking transfers.

⁹In testing our model, we will separately control for firms' age, credit history, and the number of payment records submitted to the lender.

which is equivalent to

$$p = E[z|\mathcal{I}_n] - \frac{\rho}{2} \text{Var}[z|\mathcal{I}_n], \quad (2.1)$$

where \mathcal{I}_n is the financier's information set at $t = n$. Following the literature (e.g., [Fishman and Parker, 2015](#), [Vallee and Zeng, 2019](#)), we can also interpret the reciprocal of the price p as an interest rate to map it to a lending context.

The equilibrium concept we consider is a standard sequential equilibrium. Specifically, the equilibrium profile consists of the firm's payment choice policy $x(z) : \bar{\mathbb{R}} \rightarrow \{\emptyset, X\}$, that is, whether a firm uses cash or verifiable cashless payments, and the financier's pricing policy $p : \{\mathcal{I}_n\} \rightarrow \bar{\mathbb{R}}$, and both agents maximize their expected utilities. According to sequential rationality, the financier makes inference from both 1) the actual information content of \mathcal{I}_n , and 2) the firm's decision of using cashless payments or not, that is, the strategy $x(\cdot)$ itself. The proofs are given in [Appendix A](#).

2.2 Impact of Payment Records on Optimal Financing

In this subsection, we study how the information content of verifiable cashless payments affects financing outcomes – one direction of the synergy between cashless payments and lending. We thus first consider a sub-game equilibrium in which the firm commits to using cashless payments, that is, $x(z) = X$ for all $z \in \bar{\mathbb{R}}$. In this sub-game equilibrium, observing the actual information context of X , the financier updates its belief about z directly from X only. The follow result characterizes the expected informed price by any firm type z from the perspective of $t = 0$:

PROPOSITION 1. *For a firm of type z , the expected informed financing price it gets by choosing cashless payments at $t = 0$ is*

$$p(z) \doteq \frac{\tau_z}{\tau_z + n\tau_s} \mu + \underbrace{\frac{n\tau_s}{\tau_z + n\tau_s} z}_{\text{Information-revealing}} - \underbrace{\frac{\rho}{2} \frac{1}{\tau_z + n\tau_s}}_{\text{Risk-reducing}}, \quad (2.2)$$

where $\tau_s = (\tau_x^{-1} + \tau_y^{-1})^{-1}$ captures the overall informational verifiability of cashless pay-

ments, which increases in τ_x .

The intuition behind Proposition 1 can be easily seen when comparing the informed price (2.2) to the uninformed price

$$p_\mu \doteq \mu - \frac{\rho}{2} \frac{1}{\tau_z}, \quad (2.3)$$

which is the counterfactual price that the financier offers if no firm establishes verifiable payment records at all. In this uninformed case, the financier prices the firm's technology completely based on its prior. Compared to the uninformed price (2.3), the last two terms of the informed price (2.2) show two effects by establishing verifiable payment records. We elaborate the two effects below by performing a number of straightforward comparative statics.

The first effect, which we call the *information-revealing effect*, comes from that the information context in the verifiable cashless payments, which is informative about the firm's true type, allows the financier's posterior belief to move closer to the firm's type x . Indeed, the first two terms in (2.2) represent a weighted average of the financier's prior μ and the firm's true type z , compared to the simple prior μ in (2.3). When the firm uses cashless payments for longer in the sense that n is larger, or the cashless payment service is more verifiable in the sense that τ_x is larger, the weight on the firm type z becomes larger, and consequently the informed price $p(z)$ is more reflective of z . In this sense, cashless payments are information-revealing, and the information-revealing effect is stronger when a firm establishes more cashless payment records and when cashless payments are more verifiable. We highlight that whether this information-revealing effect improves the informed price (compared to the uninformed price) depends on the firm type: only higher-than-average firm types enjoy a price improvement through this information-revealing effect.

The second effect, which we call the *risk-reducing effect*, stems from that verifiable cashless payments, regardless of the information context itself (i.e., independent of firm type), also directly reduce the financing risk that the financier has to bear. As shown in

the third term in (2.2), more payment records or payment records of higher verifiability, represented by a higher n or a higher τ_x , can directly reduce the variance when the financier makes inference about the firm type, compared to that in (2.3). The reduced risks thus encourage the financier to bid a higher financing price to the firm. As a result, the overall net effect on the firm's financing price depends on the sum of the information-revealing and the risk-reducing effects.

The results in Proposition 1 lead to three empirical predictions, which we elaborate below in three corollaries.

First, we are interested in the average effect of using cashless payments on financing outcomes. To capture the average effect, we apply Proposition 1 to compare the average expected informed and uninformed prices:

COROLLARY 1. *The average expected price improvement by all firm types is*

$$E[p(z)] - p_u = \frac{\rho}{2} \left(\frac{1}{\tau_z} - \frac{1}{\tau_z + n\tau_s} \right) > 0$$

which is increasing in n and τ_x .

The intuition behind Corollary 1 is that although the information-revealing effect is on average zero across all firm types, the risk-reducing effect is always positive. Thus, when the firm has more cashless payment records or the records are of higher verifiability, the risk-reducing effect is higher, and so is the overall price improvement. Mapped into our lending context and assuming a lender only grants a loan when the expected price is higher enough to justify the loan origination cost, we have the following prediction:

PREDICTION 1. *With more verifiable cashless payment records (or relatively, less use of cash) or payment records of higher verifiability, a firm is more likely to be granted a loan and enjoy a lower interest rate in expectation.*

Second, we are interested in the differential effect of cashless payments on financing outcomes when firm type varies:

COROLLARY 2. *A higher firm type enjoys a higher expected informed price from the financier, and the increase is higher when n or τ_x increases in the sense that*

$$\frac{\partial^2 p(z)}{\partial z \partial n} > 0 \text{ and } \frac{\partial^2 p(z)}{\partial z \partial \tau_x} > 0.$$

The intuition behind Corollary 2 is that although the risk-reducing effect is type-independent, the information-revealing effect is stronger for more extreme firm types because it allows those firms to reveal their types more clearly from the average. Particularly, when the firm has more cashless payment records or the records are of higher verifiability, this type-dependent information-revealing effect becomes even stronger. Mapped into our lending context, we have the following prediction:

PREDICTION 2. *The effects of more verifiable cashless payment records (or relatively, less use of cash) or payment records of higher verifiability in improving loan approvals and reducing interest rates are stronger for better firms, all else equal.*

Finally, we explore the effect of cashless payments on efficient capital allocation, which can be proxied by the efficiency of the financier's inference problem. As standard in the statistical literature (e.g., DeGroot, 2005), we capture it by the mean squared error $E[(z - E[z|X])^2]$. We have the following straightforward result:

COROLLARY 3. *The mean squared error $E[(z - E[z|X])^2]$ of the financier's inference is decreasing in n and τ_x .*

In our lending context, a lower mean squared error as suggested by Corollary 3 intuitively means that any residual risks not being priced becomes smaller. It then leads to a lower probability of default conditional on a given interest rate and a more efficient capital allocation. We note that, however, a lower probability of loan default does not imply a higher lender profitability in our framework, because lender competition always competes any positive profits away. Rather, because the lender is risk-averse, a lower default probability means that the lender bears less risk in equilibrium, consistent with the idea of cashless payments reducing risks.

PREDICTION 3. *More cashless payment records (or relatively, less use of cash) or payment records of higher verifiability lead to less default conditional on a given interest rate, all else equal.*

2.3 Optimal Payment Method Choice

When the financier is risk averse, the risk-reducing effect of cashless payment creates a direct incentive for borrowers to rely on cashless payments. However, as FinTech lending develops, it is natural to think that the risk-aversion of such lenders will decrease. One implication from Proposition 1 is that as the financier become less risk-averse (potentially because the financier grows larger and more diversified as the development of FinTech lenders in reality), the information-revealing effect will dominate the risk-reducing effect, and hence only high firm types can enjoy expected price improvement by committing to cashless payments. Does it imply that low firm types would deviate to use cash instead? The answer is no. When firms make the payment method choice decision $x(\cdot)$ endogenously, the financier will rationally update its belief about the firm type based on both the decision and the information content of the realized payment records X , if any. If some low type firms were to use cash in equilibrium and no payment records were established, the financier would update its belief to reflect that, which would then lead some of those firms to consider establishing payment records instead. This force will unravel and may eventually lead all firm types to adopt cashless payments when the payment records become more verifiable. We formalize this idea in this subsection by fully solving the equilibrium. This equilibrium outcome illustrates the other direction of the synergy between lending and cashless payments.

Formally, we focus on an economic scenario in which the financier's risk-aversion ρ is arbitrarily small, and consider a monotone equilibrium in which there exists a cutoff firm type z^* such that higher firm types $z \geq z^*$ commit to using verifiable cashless payments whereas lower types $z \leq z^*$ use cash, where $z^* = -\infty$ means that all firm types adopt

cashless payments.¹⁰ By sequential rationality, when firm z^* chooses cashless payments at $t = 0$, the financier knows that the firm must be of type $z \geq z^*$ at $t = n - 1$ by obtaining its submitted payment records, and by (2.1) the firm's expected financing price from the perspective of $t = 0$ is now given by

$$p(z^*; z \geq z^*) = E[E[z|X, z \geq z^*|z^*]], \quad (2.4)$$

where $p(z; z \geq z^*)$ is a function of z for any non-lower firm type $z \geq z^*$ defined as

$$p(z; z \geq z^*) \doteq E[E[z|X, z \geq z^*|z]], \quad (2.5)$$

Rather, if it chooses cash at $t = 0$ and submits no payment records at $t = n$, the financier then knows that the firm must be of type $z \leq z^*$ at $t = n - 1$. In this case, again by (2.1), the firm's expected financing price at $t = 0$ is given by

$$p(z \leq z^*) \doteq E[z|z \leq z^*], \quad (2.6)$$

and any lower firm type will get the same expected financing price. Analyzing the firm's expected payoff gain at $t = 0$ by choosing cashless payments over cash, we have the following formal result:

PROPOSITION 2. *In a monotone equilibrium such that firm types $z \geq z^*$ adopt cashless payments while firm types $z \leq z^*$ uses cash, it must be that $z^* = -\infty$, meaning that all firm types will optimally adopt cashless payments.*

The intuition of Proposition 2 can be seen from a strategic consideration among firms in the financing market that pushes all firms to adopt cashless payments. Suppose no firm uses cashless payments, in which case the financier's prior belief about the firm type is

¹⁰Note that the cutoff type z^* is indifferent from the two payment method choices, and we assume it chooses cashless payments in any equilibrium path (although it may deviate in an off-equilibrium path). Also recall that the firm type is defined over the extended real set $\bar{\mathbb{R}}$. Mathematically, this ensures that the type set is compact and thus the lowest type exists.

μ . Then all the better-than-average firms, that is, types $z > \mu$ will deviate to verifiable cashless payments, because the resulting payment information will allow them to be differentiated from the lower-than-average firms and consequently to enjoy a higher financing price. However, as they do so, the financier will rationally update its belief. The financier will now perceive the average of firm types without verifiable payment records to be lower than μ , say, $\nu < \mu$. Thus, better-than- ν firm types will deviate to cashless payments to stand themselves out from even lower firm types. This process unravels until all firm types have adopted cashless payments. Taken together, the idea behind Proposition 2 is reminiscent of the seminal “unraveling argument” of Milgrom (1981) in an information disclosure context.^{11,12}

Although Proposition 2 may seem stark as other unmodeled frictions might prevent all firms from adopting cashless payments in reality, it provides a new theoretical perspective for us to understand the increasing popularity of cashless payments and their informational efficiency in the era of big data. Cashless payment service providers offer a convenience service to their users. However, as low-creditworthiness agents understand that the payment records they create are verifiable and potentially assessed by future lenders when screening loan application, these agents might refuse to use cashless payments despite their convenience and low pecuniary cost. The potential lack of usage by low-creditworthiness agents would limit the market size and informational efficiency associated with these payment services. For this reason, regulators are also introducing policies to directly promote

¹¹In more detail, in a context of firms truthfully and voluntarily disclosing their product quality and disclosing being costless, the firm of the best quality will voluntarily disclose, and thus consumers will interpret no disclosure as indicating that the firm does not have the best quality. But given this, the second-best firm will disclose, followed by the third-best, and so on. This process unravels and all the firms thus disclose in the end. In our context, committing to using cashless payments can be indeed interpreted as committing to disclosing a series of unbiased but noisy signals about the creditworthiness of the firm to a potential financier, and the unraveling mechanism applies. Technically, our contribution here is to extend the Milgrom (1981) mechanism to a context in which the firm cannot truthfully disclose its true type directly but only through a series of unbiased but noisy signals.

¹²We note that the literature of information closure is large and there are many other circumstances in which the unraveling mechanism may fail (see Okuno-Fujiwara, Postlewaite, and Suzumura (1990) for a systematic treatment and Ali, Lewis, and Vasserman (2020), Bond and Zeng (2020) for recent applications). We draw the analogy between adopting cashless payments and information disclosure to highlight the informational role of the adoption of cashless payments, rather than suggesting that information must be fully revealed in any lending context. To study the general effect of information disclosure in lending is beyond the scope of this paper.

those services and improve their efficiency, such as the PSD2 in Europe. However, Proposition 2 suggests that those policies miss an important general equilibrium force that may ultimately push more prospective borrowers to voluntarily use cashless payments.

Broadly speaking, Propositions 1 and 2 also jointly shed light on the debates of data sharing and open banking. In our framework, firms effectively own the data of their creditworthiness before choosing their payment methods. Sharing their data by committing to using cashless payments that generate transferrable and verifiable information improves lending efficiency, consistent with the benefits of data sharing and open banking. Importantly, the synergy between FinTech lending and cashless payments we uncover suggests that the achievement of wide data sharing and open banking can be self-enforcing. More data sharing improves lending efficiency and leads to better capital allocation, which in turn encourages more data sharing due to the strategic consideration of data owners.

Although Proposition 2 and the underlying unraveling mechanism are plausible and consistent with the long-term development of cashless payments, they are hard to be directly tested empirically in the absence of long-term data combining borrower-level technology adoption and loan application. However, an indirect time-series implication of the unraveling mechanism is that better firms and firms who have a higher need to raise capital are likely to adopt cashless payments earlier than worse firms. This implication is unique in our framework because if the unraveling mechanism is not at play, we should expect the adoption decision to be independent from firm types, because such types, which are about firm creditworthiness or the need to borrow, are not correlated with the physical costs or convenience yields of cashless payments. Thus, along the time-series, all else equal (particularly, given the same information context from verifiable payment records), we expect the adoption of cashless payments to be faster and more pronounced in market segments where firms rely more on outside capital and thus have a higher incentive to become informationally appealing to future lenders.

PREDICTION 4. *The adoption of cashless payments is earlier and faster in industries or geographical areas where firms have a higher demand for outside capital, all else equal.*

3 Data and Institutional Details

3.1 Data

The empirical analysis of this study relies on novel data provided by one of the largest Indian FinTech lenders, Indifi. Indifi is an online lending platform that grants unsecured loans to micro businesses in India. To screen applications, Indifi collects information on loan applicants from several sources: from the application form on their website, from the Indian credit bureau, and from industry partners (e.g. online marketplace) for a subset of applications. A unique feature that particularly suits our analysis is that Indifi requires applicants to submit the last six monthly statements for the bank account that will be used for receiving and repaying the loan. These bank statements contain transaction level data. Our data combines all of those types of information for all loan applications received by Indifi from September 2015 to September 2019.

The aggregated dataset contains characteristics of the business applying for a loan, as well as Indifi loan characteristics when the application is successful. For all applications, we thus have information on the type of business, its industry, its location, the number of years of operations of the business, and the age of the business owner. We also observe the decision to offer a loan and for which amount and interest rate, and whether it was disbursed. We also observe whether the loan is delinquent as of September 2019.

For the majority of applications, our dataset includes the credit bureau data associated with each application. The data contains the credit score of the business owner, as well as the start date of their credit history, the number of previous loans and their associated amount and interest rate. This data also includes overdue amount on existing loans at the time at which Indifi pulled out the credit report of each of the applicant.

Providing six months of bank statements is a necessary condition for obtaining a loan from Indifi, and we therefore only keep applications that include such data. Indifi typically obtains this data by asking loan applicants to linking their bank deposit accounts to the

Indifi loan application protocol.¹³ The bank statement data is harmonized by a specialized third party, and is structured at the payment level, and therefore provides the comprehensive payment record for the applicant for the six months prior to their application.

3.2 Exploiting Bank Statement Data to Classify Payment Types

By conducting text analysis on payment descriptions, we are able to identify the technology used for the majority of payments appearing on bank statements. We group them into two broad categories: cash payments, i.e. cash deposit or withdrawal, either at a branch or an ATM, and cashless payments, which contains any payment for which we can identify the payment technology and that does not belong to the previous category.

Within cashless payments, we further distinguish between information-intensive payments and information-light payments as follows. We classify internet banking transfers and certified check payments as information-intensive and highly verifiable, as there is no aggregation and it is relatively easy to identify the name and type of the payment counterparty. We classify payments through third-party mobile applications, mobile banking and POS machine as information-light payments. Indeed, most popular mobile payment methods in India aggregate payments over a day, which prevents them from being able to identify the counterparty or the motive of a given payment. Moreover, recipient identities are often disguised by specific mobile payment IDs even in singular mobile payments. This means that most mobile payments often have lower verifiability than expected with other verifiable cashless payments.

For a small share of payments, we cannot identify the payment technology, and these payments are implicitly used as the reference point in our empirical analysis. For each borrower, we aggregate this payment level data by calculating separately for revenues and spending the share of payments conducted in cash, in verifiable cashless technology, over the six month period for which we have bank statements, and averaging these two shares.

Table 1 provides summary statistics on the application, loan and borrower characteris-

¹³Applicants can also submit pdf documents instead.

tics that we use in our empirical analysis. This table documents that applicants are micro to small firms, which rely primarily on cashless payments.¹⁴

[Insert Table 1 here]

3.3 Chest Banks and the 2016 Indian Demonetisation

On 8 November 2016, the Government of India announced the demonetisation of large banknotes, which needed to be immediately exchanged with banknotes of a new denomination. The action was intended to curtail the shadow economy and reduce the use of illicit and counterfeit cash to fund illegal activity and terrorism. The demonetisation created a large and prolonged cash shortage in the weeks that followed, with potential lasting impact on cash use.

The cash shortages triggered by demonetisation were however less pronounced at bank branches that had the status of currency chest bank. Currency chests are branches of selected banks where bank notes and rupee coins are stored on behalf of the Reserve Bank of India for further distribution of these notes and coins in their area of operations. Firms with deposit accounts at a chest bank are therefore more likely to have been able to access the new banknotes, and in turn to conduct cash payments in the wake of the unexpected demonetisation shock, all else being equal (see also [Chodorow-Reich, Gopinath, Mishra, and Narayanan \(2020\)](#) and [Crouzet, Gupta, and Mezzanotti \(2020\)](#) for detailed discussions and analysis on the broad implications). The 2016 Indian demonetisation was largely unexpected and thus could be considered as an exogenous shock to the availability of cash versus cashless payments in India. In addition, having a deposit account at a chest bank is unlikely to be directly correlated with a firm's (unobserved) creditworthiness given the wide distribution of chest banks in India and the absence of a particular benefit to bank at such a branch absent the unexpected cash shortage. We provide a list of chest banks in India in Online Appendix [A](#).

¹⁴The share of transactions done in cash is most likely underestimated, and in turn the share of cashless payment over-estimated, because applicants might receive cash from their clients, which they spend without depositing it on their bank account. This risk of a measurement error motivates instrumenting the use of cash in our empirical analysis.

4 Empirical Results

Equipped with the loan-level data and the proxies for payment information in borrowers' bank statements, we can empirically test the predictions derived in Section 2. We find supportive evidence of the economic mechanism described by our theoretical framework.¹⁵

4.1 Cashless Payments and Lending Outcomes

We empirically test Prediction 1, which results from the risk-reducing effect of using cashless payments, and estimate the relationship between the use of cashless payments and loan application outcomes.

We consider three outcome variables: an indicator variable for obtaining a loan, the interest rate paid on the loan conditional on acceptance, and the difference between this interest rate and the one obtained on the most recent loan of the applicant as per credit bureau data. The first two dependent variables capture the extensive and intensive margin of the risk-reducing effect of lender access to cashless payment records. The latter specification implicitly absorbs time-invariant characteristic observable to both lenders, and directly speak to the improvement in lending outcomes brought by processing bank statements. We regress these outcome variables on the share of cashless and cash payments, using non-classified transactions as the reference point.

Table 2 provides the regression results. We include a comprehensive set of granular controls allowing for non-linear relationships: fixed effects for industry and application month in all specifications, and fixed effects for deciles of revenues to precisely control for business size, 3-digit zip-code fixed effects, and credit score range fixed effects in column 2, 4 and 6 to further mitigate concerns that borrower characteristics potentially correlated with their use of cashless payments are driving the relationship we document.

A higher share of identified cashless payments corresponds to a significantly higher likelihood of obtaining a loan, and a significantly reduced interest rate compared to the cost of the previous loan. Conversely, a higher share of cash payments corresponds to a

¹⁵We do not explicitly test for Prediction 4 at this stage.

significantly lower probability of obtaining a loan and a higher interest rate.

The magnitude of this relationship is large: everything else equal, an interquartile increase in the share of cash transaction corresponds to a likelihood that is $0.12 \times 22 = 2.6$ percentage points lower to get approved, which represents more than 10 percent the baseline likelihood of getting approved. In terms of interest rates, an interquartile increase in cash payments corresponds to an interest rate that is higher by 60 basis points.

[Insert Table 2 here]

In addition, we test whether Prediction 1 fully holds in the data, namely that the likelihood of getting a loan is also increasing the number of transactions n appearing in the payment record. While in the model cash transactions do not appear at all on record, in real life statements illustrate both cash and cashless transactions. However, due to the higher verifiability of cashless transactions, lending outcomes should be more sensitive to the number of these types of transactions than to the total number. We therefore regress the previous lending outcomes on the log of the total number of transactions appearing on bank statements, and on the log of the number of verifiable transactions. Results are displayed in table 3. We find that the number of verifiable transactions, which we interpret as the empirical counterpart to n in the model, relates to lending outcomes beyond the total number of transactions appearing on the statements. Controlling for the total number of transactions, a larger number of verifiable ones is associated with a significantly higher likelihood of getting a loan, and a significantly lower interest rate. We interpret this result as further empirical support for the economic mechanism we model in Section 2.

[Insert Table 3 here]

4.2 Cashless Payments, Borrower Type, and Lending Outcomes

Prediction 2 provides an interaction test: using cashless payment should have more of a positive impact on high quality borrower, as they benefit from both the risk-reducing channel, as all borrowers do, and the information-revealing channel, which benefits good

borrowers and hurt bad borrowers. To test this prediction, we use the volatility in revenues, observed on bank statements, as a proxy for borrower type that is not captured by the credit score.¹⁶ Specifically, everything else equal, including the amount of monthly revenue, which proxies for size, a higher revenue volatility is suggestive of a higher risk / lower type borrower.

We therefore interact our measure of use of cashless payments with this risk proxy in the previous specification. Results are displayed in Table 4. The findings are consistent with Prediction 2: using cashless payments is particularly beneficial to low risk firms. Specifically, for applicants with a low revenue volatility, a higher use of verifiable cashless payments leads to an even higher likelihood of the loan application being approved than for borrowers with a high revenue volatility. This relationship is unlikely to be driven by other firm-level characteristics given the comprehensive set of fixed effects that we include. Column 2 and 3 suggest that this effect is also present at the intensive margin, i.e. on loan pricing, although the interaction coefficients are not statistically significant, possibly due to the smaller sample.

[Insert Table 4 here]

The results in Table 2 and 4 provide direct evidence that outside bank statement data, by documenting transferrable and verifiable payment information, can affect the lending outcome at another lender that has access to this data. Such impact appears to follow two channels: the risk-reducing and information revealing effects of accessing and exploiting such data. These findings thus directly speak to the motives behind the recent policy initiatives that aim to promote data sharing and open banking, such as the PSD2. Notably, our findings show that what matters for lending outcomes is not only bank statement aggregates. Rather, the detailed components of these statements matter in terms of how much verifiable information such statements contain, as we capture by the relative share of cash versus cashless payment records.

¹⁶The credit bureau does not observe revenues, nor its volatility.

4.3 Verifiability of Cashless Payments and Lending Outcomes

Having analyzed the effects of cashless payments on lending outcomes, we zoom in to examine how different types of cashless payments, varying in their level of verifiability, may further impact lending outcomes at a more granular level. Consistent with Prediction 1, we expect cashless payments with a higher level of verifiability to facilitate loan screening, and we expect the resulting lending outcomes in terms of loan approval and interest rate offering to be better for borrowers.

Following our classification of different type of cashless payments, we further breakdown our measure of use of cashless payments into the use of information-intensive technologies and information-light technologies. Information-intensive technologies include for instance online banking or certified checks: each payment record corresponds to a single payment, and the counter-party can be identified. These information-intensive payment technologies thus generate payment records of higher verifiability, or high ρ_x in the model. On the other hand, information-light technologies, such as mobile payment apps, typically aggregate or net several payments within a day, and prevent the counter-party from being identified. Accordingly, we interpret these information-light payment technologies to generate payment records of lower verifiability, or low ρ_x in the model.

We run the specifications of Tables 2 and 4 based on this breakdown of cashless payments. The results are displayed in Table 5. They show that more use of information-intensive payments leads to a higher likelihood of loan approval and a lower offered interest rate, while in contrast, more use of information-light payments leads to a lower likelihood of loan approval and a higher offered interest rate. The results are both statistically and economically significant. Also consistent with the result in Table 4, for higher-type borrowers with a lower revenue volatility, more use of information-intensive cashless payments increases the likelihood of loan approval and decreases the offered interest rate even more. Overall, our findings are consistent with Prediction 1 and suggest that the impact of cashless payments on lending outcomes is not only present at the extensive margin between cash and cashless payments, but also present at the intensive margin among different cashless

payments.

[Insert Table 5 here]

4.4 Causal Evidence

Although Proposition 2 suggests that firms' payment method choices should be independent to their creditworthiness, one might worry that other unobservable firm characteristics may at the same time drive firms' payment choices and borrowing outcomes. To mitigate this concern, we implement an instrumental variable analysis using the unique feature of our bank statement data.

Specifically, we restrict our sample to loan applications submitted after the 2016 Indian demonetisation, and instrument the share of payments in cash on bank statements with an indicator variable for the borrower banking at a currency chest bank.¹⁷ The rationale of the instrument is that because shortages of cash following the demonetisation were less pronounced at chest banks, their clients should rely relatively more on cash, everything else equal, as they had a lower incentives to switch to cashless payments. The exclusion restriction is likely to be satisfied due to the unexpected and exogenous nature of the demonetisation shock. We mitigate concerns over composition effects between chest bank clients and other bank clients by including a comprehensive list of precise controls, including firm revenues, industries, and geographical regions. The identifying assumption is therefore that the matching between small firms and chest bank is orthogonal to firm quality that is unobservable to the econometrician, but observable to Indifi.

We present the regression coefficients for both stages of the 2SLS in Table 6. This first-stage regression coefficient is large and statistically significant: it indicates that having a deposit account at a chest bank increases the use of cash payments by 3 percentage points on average. The F-stat for the first stage is larger than 40. The second-stage result is consistent with the OLS analysis: based on this plausibly exogenous variation in the use of cash payments at the borrower level, we find that more use of cash payments leads to

¹⁷We are able to identify the bank branch by combining the bank name with the borrower zipcode.

a significantly lower likelihood of loan approval. The economic magnitude is particularly large. A interquartile increase of cash payments, which represent 22 percentage points in our sample, is associated with a $0.6 * 22 = 13p.p.$ decrease in the chance of getting a loan approved.

Such analysis supports a causal interpretation of the test we previously run for prediction [1](#).

[Insert Table [6](#) here]

4.5 Cashless Payments and Defaults

We move on to empirically test Prediction [3](#) by relating the use of cashless payments to loan defaults. If cashless payments lead to more efficient loan screening and pricing, we should expect that a borrower' credit risk is better priced in at loan issuance. In other words, controlling for interest rates, we expect the loan default rate to be lower.

To test this prediction, we regress an indicator variable of a loan being defaulted in our sample on the shares of cash and cashless payments. Consistent with Prediction [3](#), we find that more use of cash, which is not verifiable, leads to a higher likelihood of loan default conditional on an interest rate. This finding suggests that the use of cash leads to less efficient screening and lending decisions. Despite more cash payments leading to both higher likelihood of loan rejections and higher interest rates, the credit risks have still not been fully priced yet.

At the same time, we do not find significant predictive power of the share of verifiable cashless payments on loan defaults. Combined with the results in Tables [2](#) and [4](#), this finding suggests that, compared to cash, cashless payments lead to more efficient lending decision, and any additional information context from a marginal verifiable payment record has been relatively priced in by the offered interest rate.

[Insert Table [7](#) here]

5 Conclusion

We provide a new perspective to understand the joint rise of FinTech lending and cashless payments. We uncover both theoretically and empirically a synergy between FinTech lenders and cashless payment providers, the latter producing borrower information outside the lender. In one direction, FinTech lenders become more efficient in screening high-versus lower-quality borrowers when borrowers adopt cashless payments that produce more verifiable information. In the other direction, because would-be borrowers expect lenders to rely on outside verifiable payment information to screen them, a strategic consideration for a borrower to stand out of worse borrowers emerges, which ultimately pushes all borrowers to adopt cashless payments.

We use novel data from a large FinTech lender in India to test our predictions. We find that a higher use of cashless payments is associated with improved borrowing outcomes: applicants relying heavily on cashless payments are more likely to obtain a loan, and when doing so obtain a lower interest rate. Consequently, such borrowers get significantly lower rate from the FinTech lender than from previous loans with traditional institutions. This benefit is particularly pronounced for cashless payment users that present a low level of risk, due to the combination of both risk-reducing and information-revealing effects of verifiable payment records. These relationships appear to be more pronounced when focusing on more verifiable cashless payments. We also find that within loans charging the same interest rate, borrowers that use cash more are more likely to default.

The mechanism we uncover provides a plausible explanation for the hand-in-hand rise of both FinTech lending and cashless payments, and also suggests an alternative banking model without a balance sheet and without relationships in the traditional sense. This mechanism further sheds light on the recent policy developments in data sharing and open banking. It first provides a direct support to data sharing and open banking in term of improving lending efficiency. Notably, our findings show that what matters for lending outcomes is not bank statement themselves. Rather, the detailed components matter in

terms of how much information is verifiable, as we capture by the relative share of cash versus cashless payment records. It also implies that even without policies to promote data sharing or open banking such as the Second Payment Services Directive (PSD2) in Europe, borrowers may voluntarily commit to data sharing in order to improve their outcome on the lending markets.

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Table 1: **Summary Statistics**

Panel A. Loan Applicant Characteristics				
	Obs	Mean	p25	p75
Year of Application	86,447	2018	2018	2019
Applicant Age	86,443	35.3	29.1	40.4
Business Age	85,916	4.8	1.4	5.9
Cibil Score	86,447	534	562	715
Credit History Length (in Years)	63,433	7.0	2.4	11.1
Panel B. Banking Statement Data				
Share of Cashless Payments	86,397	0.515	0.376	0.668
<i>of which: Information-intensive Payments</i>	86,397	0.384	0.215	0.531
Share of Cash Payments	86,397	0.198	0.070	0.298
Borrower Banks at Chest Banks (0/1)	86,447	0.041	0	0
Avg. Monthly Revenue (INR)	86,418	615,696	114,154	823,622
Panel C. Loan Application Outcomes				
Approved Loan (0/1)	86,447	0.252	0	1
Offered Interest Rate	21,746	24.8	23.4	27
Δ Interest Rate	2,897	1.49	-11	13
Default (0/1)	9,138	0.073	0	0

Notes: This table reports summary statistics for main variables used in the regressions. Panel A reports loan consequences of the applications with available banking records. Panel B displays summary statistics of banking payments of applicants by intensity of information of payment technologies, bank type, monthly average revenue and credit score.

Table 2: **Payment verifiability and borrowing outcomes**

	Approved Loan (1/0)		Offered Interest Rate		Δ Interest rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of verifiable cashless payments	0.019*	0.018*	0.025	0.085	-2.445*	-2.332*
	(0.010)	(0.010)	(0.106)	(0.112)	(1.377)	(1.256)
Share of cash payments	-0.153***	-0.122***	2.766***	2.596***	3.707*	1.624
	(0.018)	(0.017)	(0.217)	(0.218)	(1.930)	(1.869)
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	53,065	52,719	17,608	17,550	2,887	2,821
R ²	0.260	0.311	0.447	0.491	0.057	0.185

Notes: This table presents OLS regressions that use share of payments of different level of traceability to predict loan consequences. The set of controls includes Log # of payments, credit history length, business vintage, Log of owner's age, missing credit score indicator and top-up loan indicator. Standard errors are clustered at application-month level.

Table 3: Number of transactions on payment records

	Approved Loan (1/0) (1)	Offered Interest Rate (2)	Δ Interest rate (3)
log(# of transactions)	0.101*** (0.007)	-0.175** (0.079)	0.273 (0.975)
log(# of verifiable transactions)	0.015*** (0.004)	-0.159*** (0.044)	-1.167 (0.838)
Controls	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes
Anchor type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Application Month FE	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	52,718	17,550	2,821
R ²	0.312	0.491	0.186

Notes: This table presents OLS regressions that use the number of payments of different level of traceability interacted with two risk measures to predict loan consequences. The set of controls includes credit history length, business vintage, Log of owner's age, missing credit score indicator and top-up loan indicator. Standard errors are clustered at application-month level.

Table 4: Payment verifiability, borrower risk, and borrowing outcomes

	Approved Loan (1/0) (1)	Offered Interest Rate (2)	Δ Interest rate (3)
Share of verifiable cashless payments	0.025* (0.013)	-0.048 (0.147)	-2.899 (1.798)
Share of cash payments	-0.123*** (0.017)	2.604*** (0.222)	1.867 (1.885)
Share of verifiable cashless payments \times Weekly revenue volatility	-0.191** (0.093)	3.399 (2.525)	18.176 (29.320)
Weekly revenue volatility	-0.507*** (0.061)	-3.333* (1.794)	11.060 (17.918)
Controls	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes
Anchor type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Application Month FE	Yes	Yes	Yes
Cibil score group FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	52,718	17,550	2,821
R ²	0.312	0.491	0.186

Notes: This table presents OLS regressions that use share of payments of different level of traceability interacted with two risk measures to predict loan consequences. The set of controls includes Log # of payments, credit history length, business vintage, Log of owner's age, missing credit score indicator and top-up loan indicator. Standard errors are clustered at application-month level.

Table 5: **Verifiability Intensity**

	(1)	(2)	(3)	(4)
	Approved Loan (1/0)	Loan offered indicator	Offered Interest Rate	Offered Interest Rate
Share of information-intensive payments	0.120*** (0.009)	0.148*** (0.013)	-0.773*** (0.098)	-0.962*** (0.142)
Share of information-light payments	-0.143*** (0.010)	-0.150*** (0.009)	0.888*** (0.176)	0.871*** (0.175)
Share of information-intensive payments \times revenue vol.		-0.501*** (0.125)		4.683* (2.732)
Weekly revenue volatility		-0.485*** (0.061)		-3.724** (1.760)
Controls	Yes	Yes	Yes	Yes
Revenue deciles FE	Yes	Yes	Yes	Yes
Anchor type FE	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
Region FE	Yes	Yes	Yes	Yes
Interest Rate FE	No	No	No	No
Observations	52,719	52,718	17,550	17,550
R ²	0.315	0.317	0.486	0.486

Notes: This table presents OLS regressions that use share of payments of different level of information intensiveness to predict loan consequences. The set of controls includes Log # of payments, credit history length, business vintage, Log of owner's age, missing credit score indicator and top-up loan indicator. Standard errors are clustered at application-month level.

Table 6: **IV: Payment verifiability and loan approval**

	(1)	(2)
	Share of Cash Payments	Approved Loan (1/0)
Borrower banks at Chest Bank (1/0)	0.027*** (0.004)	
Share of Cash Payments (instr.)		-0.599* (0.322)
Controls	Yes	Yes
Revenue deciles FE	Yes	Yes
Anchor type FE	Yes	Yes
Industry FE	Yes	Yes
Application Month FE	Yes	Yes
Cibil score group FE	Yes	Yes
Region FE	Yes	Yes
Observations	51,151	51,151
R ²	0.171	0.005

Notes: This table presents regression coefficients for a 2SLS specification. Column 1 presents the first stage, where we regress $\%paymentsincash$ on an indicator variable for the borrower banking at a chest bank. Column 2 displays the second stage, where we regress the indicator variable for getting the loan application approved on the instrumented *Share of Cash Payments*.

Table 7: **Payment verifiability and loan default**

	(1)	(2)
	Default (1/0)	
Share of verifiable cashless payments	0.003 (0.015)	0.005 (0.015)
Share of cash payments	0.118*** (0.029)	0.094*** (0.026)
Controls	No	Yes
Revenue deciles FE	No	Yes
Anchor type FE	No	Yes
Industry FE	No	Yes
Application Month FE	Yes	Yes
Cibil score group FE	No	Yes
Region FE	No	Yes
Interest Rate FE	Yes	Yes
Observations	9,084	8,139
R ²	0.055	0.115

Notes: This table presents OLS regressions that use share of payments of different level of information intensiveness interacted with revenue volatility to predict loan consequences. The set of controls includes Log # of payments, credit history length, business vintage, Log of owner's age, missing credit score indicator and top-up loan indicator. Standard errors are clustered at application-month level.

Appendix

A Proofs

Proof of Proposition 1. When the firm adopts verifiable cashless payments, the financier makes inference about the firm type based on the established and submitted payment records X . We first note that

$$x_t|z \sim N(z, \tau_s^{-1}),$$

where $\tau_s \doteq (\tau_x^{-1} + \tau_y^{-1})^{-1}$ captures the effective overall informational verifiability of each payment record. By Bayesian updating, we then have

$$z|X \sim N\left(\frac{\tau_z \mu + n\tau_s \bar{x}}{\tau_z + n\tau_s}, \frac{1}{\tau_z + n\tau_s}\right),$$

where $\bar{x} = \frac{1}{n} \sum_{t=0}^{n-1} x_t$ is the sample mean of X . On the hand, note that $E[\bar{x}|z] = E[x_t|z] = z$. We then immediately have

$$E[E[z|X]|z] = \frac{\tau_z \mu + n\tau_s z}{\tau_z + n\tau_s},$$

and

$$E[Var[z|X]|z] = \frac{1}{\tau_z + n\tau_s}.$$

yielding the result. All the three corollaries then follow by direct calculation.

Proof of Proposition 2. We consider $\rho = 0$ to focus on the economic environment where the information-revealing effect dominates. When the cutoff firm type z^* adopts cashless payments, (2.4) suggests that the expected financing price from the perspective of $t = 0$ is

$$p(z^*; z \geq z^*) = E[E[z|X, z \geq z^*|z^*] \geq p(z^*),$$

where $p(z^*)$ is given by (2.2) in Proposition 1 under $\rho = 0$. On the other hand, if the cutoff

firm type z^* uses cash, (2.6) suggests that the expected financing price from the perspective of $t = 0$ is

$$p(z \leq z^*) = E[z|z \leq z^*] = \mu - \frac{\phi(\zeta^*)}{\Phi(\zeta^*)}\sigma,$$

where $\sigma = \sqrt{\tau_z^{-1}}$ is the prior standard deviation, $\zeta^* = \frac{z^* - \mu}{\sigma}$ is the standardized cutoff firm type given the prior distribution, and

$$\phi(\zeta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\zeta^2\right),$$

and

$$\Phi(\zeta) = \frac{1}{2} \left(1 + \operatorname{erf}\left(\frac{\zeta}{\sqrt{2}}\right)\right),$$

are the probability density function and the cumulative distribution function of a standard normal distribution.

Define

$$\Delta(z^*) \doteq p(z^*; z \geq z^*) - p(z \leq z^*)$$

as the expected payoff gain at $t = 0$ for the cutoff firm type z^* by choosing cashless payments over cash. Direct calculation yields:

$$\begin{aligned} \Delta(z^*) &\geq p(z^*) - p(z \leq z^*) \\ &= \left(\frac{n\tau_s}{\tau_z + n\tau_s}\zeta^* + \frac{\phi(\zeta^*)}{\Phi(\zeta^*)}\right)\sigma, \end{aligned} \tag{A.1}$$

where again $p(z^*)$ is given by (2.2) in Proposition 1 under $\rho = 0$. Further define

$$M(\zeta^*) \doteq \frac{\phi(\zeta^*)}{\Phi(\zeta^*)} > 0.$$

By standard statistical result (e.g., Gordon, 1941), we know that $M(\zeta^*)$ has the following properties:

i). $\lim_{\zeta^* \rightarrow -\infty} (\zeta^* + M(\zeta^*)) = 0,$

ii). $-1 < M'(\zeta^*) < 0$, and

iii). $M''(\zeta^*) > 0$,

the three of which jointly imply that

$$\zeta^* + M(\zeta^*) > 0 \tag{A.2}$$

for any $\zeta^* > -\infty$. Because $\frac{n\tau_s}{\tau_z + n\tau_s} < 1$, (A.1), (A.2) and property i) above then jointly imply that $\Delta(z^*) > 0$ for all $-\infty \leq \zeta^* < 0$. On the other hand, (A.1) also directly means that $\Delta(z^*) > 0$ holds for all $\zeta^* \geq 0$. Thus, $\Delta(z^*) > 0$ for all $z \in \overline{\mathbb{R}}$. Finally, note that $p(z; z \geq z^*)$ increases in z by construction (2.5), confirming that a monotone equilibrium exists only if $z^* = -\infty$, concluding the proof.

Online Appendix for
FinTech Lending and Cashless Payments

A List of Indian Chest Banks

• Public sector banks

1. Allahabad Bank
2. Bank of Baroda
3. Bank of Maharashtra
4. Central Bank of India
5. Dena Bank
6. Indian Bank
7. Punjab & Sind Bank
8. State Bank of India
9. Andhra Bank
10. Canara Bank
11. Bank of India
12. Corporation Bank
13. Indian Overseas Bank
14. Oriental Bank of Commerce
15. Punjab National Bank
16. Syndicate Bank
17. UCO Bank
18. United Bank of India
19. Union Bank of India
20. Vijaya Bank
21. State Bank of Bikaner & Jaipur
22. State Bank of Patiala
23. State Bank of Indore
24. State Bank of Travancore
25. State Bank of Hyderabad
26. State Bank of Mysore
27. State Bank of Saurashtra

• Private sector banks

1. Bank of Punjab Ltd.
2. The Bank of Rajasthan Ltd.
3. Catholic Syrian Bank Ltd.
4. The Dhanalakshmi Bank Ltd.
5. The Federal Bank Ltd.
6. HDFC Bank Ltd
7. ICICI Bank Ltd.
8. IDBI Bank Ltd.
9. The Jammu & Kashmir Bank Ltd.
10. The Karnataka Bank Ltd.
11. The Karur Vysya Bank Ltd.
12. The Lakshmi Vilas Bank Ltd.
13. The South Indian Bank Ltd.,
14. Tamilnad Mercantile Bank Ltd.
15. UTI Bank Ltd.
16. The Ing Vysya Bank Ltd.
17. Standard Chartered Bank
18. Rajasthan Co-op Bank Ltd.