Fintech Lending and
Sales Manipulation

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Abstract

Weak debt enforcement is a challenging issue, especially in small-firm lending. Fintech payment companies acting as lenders possess a potential solution to weak debt enforcement. Their location in the payment chain yields them a senior position in the digital revenue stream of the borrowing merchant, as the payment company can deduct part of the merchant's sales it processes to amortize the loan. Our analysis of the transactions processed through a fintech company in India offering such sales-linked loans suggests that some borrowers strategically default by diverting their digital sales away from the company. Sales diversion manifests as a discontinuous drop in borrowing merchant's transactions immediately after the loan disbursal. Mapping fintech-loan data with the credit bureau scores sourced independently, we find that sales diversion is more common among borrowers with higher credit scores i.e., borrowers with better access to the credit market. Using the spatial and temporal heterogeneity in cash availability generated by a cash-crunch episode, we find that manipulating borrowers employ cash as an alternative payment instrument to divert their digital sales.

JEL Classification: G20, G21, G23
Keywords: Fintech lending, Limited enforcement, Sales manipulation, Regression discontinuity

1 Introduction

Information asymmetry and limited enforcement create hurdles for firms wanting to access credit. These problems are particularly severe for micro, small and medium enterprises (MSMEs). Lenders find it hard to assess the creditworthiness of MSMEs owing to the latter's small scale and opaque nature of business. Additionally, relatively small loan sizes and slow judicial processes make it costlier for lenders to enforce payments from MSME borrowers, and that fact deters lenders from serving MSMEs in the first place. These frictions have resulted in severe credit constraints for MSMEs.[1]

Financial technology (fintech) is commended for its potential to alleviate the informational frictions by making use of non-traditional data sources and models that help lenders screen the borrowers better (Frost et al., 2019; Hau et al., 2019; Jagtiani and Lemieux, 2019). In this paper, we analyze another potential advantage of fintech: the mitigation of enforcement problems when the fintech lender is also a payment processing company.

Fintech payment companies[2] process *digital* payments between a merchant (seller or firm) and its customers (buyers). The payment company, thus, not only observes revenue (from electronic payments) of the merchant but also sits between the payments made by the customers and receipt of those payments by the merchant. Therefore, if the payment company also acts as a lender to the merchant, the company can enforce the repayment of the loan by taking a *cut* from the digital revenue stream of the borrowing merchant, giving the company ultimate seniority over digital part of the merchant's income. This arrangement bypasses the need for institutional enforcement of credit contracts (such as through courts) and can be highly effective in scenarios where enforcement is costly.

However, this mechanism is effective only to the extent merchants do not have the ability (or the intent) to divert their electronic sales away from the lending payment company, for example, by persuading their customers to pay in cash instead. If the diversion is feasible and attractive, the borrowing merchant may use that strategy to willfully default or delay the repayment.

In this paper, we study such an example from a major Indian fintech payment company that lends to merchants who use its point of sales (POS) machine for accepting digital payments. Using the loan-level and transaction-level data, we find that borrowing merchants *discontinuously* drop their electronic sales[3] immediately after the loan disbursal. Given that

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[1]According to the World Bank, about 48% of MSMEs in developing countries are credit constrained, with the credit deficit aggregating to about USD 5.2 trillion and amounting to 19% of their GDP (Bruhn et al., 2017). According to Boata et al. (2019), the financing gap for SMEs is about EUR 400 billion in the Eurozone, accounting for 3% of its GDP, while in the United States, the SME financing gap is about 2% of the GDP.

[2]Examples of such companies are PayPal and Square in the USA and Ant Financial in China.

[3]We use the term, *transactions* and *sales* to mean *electronic transaction value* and use these terms interchangeably. Similarly, we mean electronic/digital transactions when we say *transactions*. In any context when the terms *sales* or *transactions* refer to something other than electronic transactions, it is explicitly mentioned.

this discontinuity is consistently observed over loans made at different points of time, we associate this discontinuous fall in sales to manipulation (diversion of sales) by the borrowing merchants. Further evidence for active manipulation lies in the nature of the discontinuity. First, this behavior is exhibited by repeat borrowers and only in their second loan and subsequent loans. The repeat borrowers, in their first loan or the non-repeat borrowers do not exhibit any suspicious discontinuity post-disbursal. Second, only those repeat loans that go into default or in delay (together *non-performing loans*) show a discontinuity. Performing loans that are neither in default nor in delay show no discontinuity. Third, the repeat borrowers whose repeat loans turn out to be non-performing tend to show a weakly increasing trend in sales, before discontinuously dropping sales after disbursal. On the other hand, borrowers exhibiting no discontinuity in sales, such as the repeat borrowers on their first loans or on their performing loans, do not show an upward trend in sales pre-disbursal. Indeed, these borrowers show a slight decline in sales before disbursal.

Because performing loans are not associated with any discontinuity, we conclude that sales diversion post-disbursal may be used only to a limited extent to manage short-term liquidity needs. The observed discontinuity in sales of the borrowers with delayed loans suggests that one motive for sales manipulation is to turn a short-term loan into a long-term loan. This behavior basically means that through manipulation, the merchants avoid an upward-sloping yield curve. Finally, borrowers with defaulting loans showing discontinuity in sales indicate that there is a voluntary element in default.

We also consider alternative explanations for observed discontinuities and show that no explanation other than sales manipulation is valid in the light of the evidence. The first alternative explanation is that at the time of loan disbursal, the borrowers might have coincidentally been hit by a shock that shows up as discontinuity. If such a shock were due to some common factor (aggregate shock), we would observe it for the whole sample. We observe discontinuity for the non-performing repeat loans that were *disbursed on the same dates* as the non-performing first loans. The latter do not show a discontinuity. Further, we also find that among the repeat loans, the non-performing loans show a discontinuity in sales while the performing loans *disbursed on the same dates* don't–again ruling out any aggregate shock.

Another alternative explanation could be in terms of borrower-specific (idiosyncratic) factors. Such an explanation would link discontinuity to the realization of some borrower-specific *expected shock*. This alternative explanation suggests that there is selection into loans based on anticipation of shocks and borrowing merchants showing discontinuity is simply the manifestation of the realization of that expected shock on the day of disbursal. However, it will be extremely hard to reconcile this explanation with the observed nature of discontinuity. First, if firms took loans in anticipation of a shock, the realizations of the shocks should be distributed on both sides of the disbursal date because there is no perfect certainty about either the exact disbursal date or the exact arrival date of the shock. In such a case, observing discontinuity right on the disbursal date would imply that merchants are exceptionally good at predicting

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the timing of an expected shock such that it coincides with disbursal. Second, discontinuity follows a weakly increasing trend in sales. This would imply that merchants somehow can not only predict the timing of the negative shock well but can also do so when facing increasing or stable sales.

We study borrowers' sales behavior in a narrow window around loan disbursal and use regression discontinuity (RD) design to quantify the drops in digital sales of the borrowing merchants post-disbursal. Our RD estimates in a seven-day window around disbursal suggest that non-performing borrowers in their repeat loan drop their sales, right after disbursal, by about 18 percentage points, reducing the sales to about 17% below their long-term average daily sales. This amount is an economically meaningful drop. Within the non-performing loans, the defaulting borrowers show a higher drop in sales. Their sales drop by 21 percentage points immediately after loan disbursal. Interestingly, defaulting loans also show higher-than-average sales pre-disbursal. Their sales are about 5% higher than their long-term average on the eve of disbursal but fall to 16% below the long-term average upon disbursal. The late loans, on the other hand, show a drop by 17 percentage points. The drop is also mirrored in the number of transactions, and the non-performing repeat borrowers divert about 11% of their transactions right after disbursal compared to the pre-disbursal levels. These results hold in various longer bandwidths as well.

We also relate sales manipulation by borrowers to credit market competition. Theoretically, competition weakens loan enforcement by creating *enforcement externality* as existence of multiple sources of funding diminishes the borrower's value of a relationship with a lender and incentivizes the borrower to default willfully (Hoff and Stiglitz, 1998; Shapiro and Stiglitz, 1984). Our setting allows us to study this relation. Owing to its exclusive reliance on historical sales data, our payments company never used credit scores of the borrowers for making lending decisions. It also did not report credit performance to any credit bureau. This setting, therefore, provides us the unique opportunity to link sales diversion with the borrower's outside options captured by the borrower's credit score.

We divide our sample of borrowers into two groups based on the threshold level of credit score that the credit market considers being the demarcation between high and low credit quality. We also have a third category of borrowers–those with no credit history. We can think of those borrowers with credit scores above the threshold as the ones having easy access to credit outside of their credit relationship with the payment company. Therefore, such borrowers are more likely to default willfully. In contrast, borrowers with a low credit score or no credit history are less likely to default willfully. In line with this, we find that defaulting borrowers who have credit scores above the threshold show very large disbursal-day discontinuity in sales. These defaulting merchants also show approximately 25% higher sales than average before disbursal and then reduce sales by approximately 40 percentage points immediately following the disbursal. Such large discontinuity points to a diversion in sales and a voluntary default. The merchants with credit scores lower than the threshold or merchants with no credit history

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do not show discontinuity when in default.

To be sure, in the setting with POS lending, enforcement can be resurrected even in the presence of a competitive *lending market*, because it inhibits the borrower's *ability to default* by allowing the lending payment company to effectively take a *senior position* in the digital revenue stream of the borrower. However, the evidence that borrowers can still default by manipulating their sales implies that borrowers can divert their sales away from the lending payment company's system to some alternative channel. Therefore, the seniority of the payment company can be *diluted* due to the competitive *payment market*–i.e., due to the competition faced by the electronic payment company from cash, other payment technology or other payment companies.

To answer whether borrowing merchants divert their sales to cash or to other digital means (such as the POS machine of competing payment companies), we use the exogenous shock in availability of cash that occurred in March-April 2018 in certain regions of India. These regions faced a temporary *cash crunch* as ATMs ran dry. A cash crunch makes it harder for firms to persuade their customers to pay in cash. Therefore, if we observe that the borrowing merchants display the same kind of sharp downward jump in digital sales in the crunch period as they do in other periods, it would imply that merchants mainly use other digital means to divert sales from their lender's platform. We find that borrowers from districts affected by the cash crunch show no significant discontinuity at disbursal in the cash crunch period, while they show a significant drop in sales in the non-crunch period. Further, borrowers in non-crunch districts always show a discontinuity, whether in the crunch period (that affected crunch districts) or non-crunch period. These results indicate that borrowers use cash, at least partly, to divert sales.

Our results point out that even though payment company lending has the potential to improve enforcement by making loan repayment *automatic at source*, it is not a foolproof mechanism, yet. Its potential is evident from the fact that the payment company is able to lend to MSMEs with no or limited credit history, that would find it extremely hard to access credit otherwise. The limitations emanate from the existence of competing payment technologies (including cash) that can be used to divert sales away from the lending payment company. Thus, as long as debt enforcement institutions remain weak, and if economies rely predominantly on cash, enforcement is going to be challenging. However, as economies digitize more rapidly with digital means of payment replacing cash, payment companies will be able to play a more and more pivotal role in debt enforcement.

The literature on fintech credit so far has mainly focused on consumer lending by the platform-based fintech lenders. The papers in this theme have mainly documented the fintech lenders' ability to use alternative data and machine learning techniques. Some notable papers in this theme include Di Maggio and Yao (2020), Jagtiani and Lemieux (2019), Agarwal et al. (2019) and Berg et al. (2020), and Gambacorta et al. (2019). Other papers document the emergence of fintech-based lenders and how they are changing the landscape of the MSME and

household loan markets. The focus of this line of research is to describe how the fintech-based lenders interact with traditional lenders at an aggregate level (Buchak et al., 2018; Fuster et al., 2019; Gopal and Schnabl, 2020).

Our paper looks at MSME loans and specifically highlights the use of payment technology in MSME loan underwriting as well as in loan repayment enforcement. The literature studying payment fintech and the lending business is just beginning to emerge. The only related work in this area has covered bigtech companies like Alibaba and Mercado Libre. Bigtechs are large technology companies that have a major non-financial business, such as e-commerce platforms, but have ventured into payments and lending. Another prominent example of a bigtech in the payment and lending business is Amazon.[4] The research on bigtechs has so far studied their ability to use past sales data of MSMEs for credit screening and their role in enhancing MSME growth and access to financial services (Frost et al., 2019; Hau et al., 2019, 2017).

In this paper, we look at the payment fintech companies. As opposed to bigtech, their main business is to offer financial services such as payments and credit with the application of state-of-the-art technology. Further, in contrast to the existing papers on bigtech financing, we focus on the enforcement of loan contracts by payment fintech companies due to their ability to potentially acquire seniority in the sales flow of the borrowing MSME. Indeed, it could be that loan enforcement is a less serious issue for bigtechs because they enjoy almost complete monopoly power over the merchants who sell through their e-commerce platforms. Therefore, for the bigtech lenders, the threat to exclude any defaulting borrower from the platform is already a strong enforcement device. Payment fintechs, on the other hand, are payment service providers to MSMEs that have substantial physical operations. Payment fintech companies operate in a more competitive environment. Understanding the consequences of competition in credit and payment markets on enforcement is an important part of our study. Another difference between our work and the studies on bigtech credit is that we have access to highly granular data at the transaction (card swipe) level, and, therefore, we can study borrowing and non-borrowing merchants very closely. This granularity helps us to scrutinize any immediate change in the sales patterns of borrowers. The studies on bigtech credit have used data aggregated over monthly frequency and therefore cannot drill into the short-term responses of borrowers to events such as loan disbursal.

This paper is organized as follows. Section 2 provides a background about fintech lending and debt enforcement. Section 3 discusses the institutional set-up of the lending program with sales-linked repayment. Section 4 explains our data and presents our empirical strategy. Section 5 presents our results with visual and econometric evidence on discontinuity. Within this section, we present results relating to enforcement challenges under a competitive debt market in Section 5.3 and from competitive payment technology in Section 5.4. Section 6 concludes the paper.

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[4]See BIS annual economic report 2019 for a discussion about bigtechs and their entry into the payment and lending markets (BIS, 2019).

2 Payment Fintech and Credit Enforcement

Studying the MSME credit market and its link with payment fintech is interesting for several reasons. First, payment services is the first major part of the financial industry disrupted by fintech (Bech and Hancock, 2020; Petralia et al., 2019; Philippon, 2016; Rysman and Schuh, 2017). Fintech has reduced the cost of transactions drastically, which is why digital payments are perceived as the vehicle to financially include the unbanked or under-banked parts of the economy (BIS and World Bank, 2020).

Second, major fintech payment companies across the world have started offering credit to merchants on their network. In the United States, Paypal and Square are leading payment companies offering credit to MSMEs that use their online payments services or POS machines. Square has even acquired a banking license to grow its merchant lending business. Tyro payments in Australia also received a full banking license in 2016 with an authorization to operate as a deposit-taking institution. In Europe, iZettle, a Swedish payment company in the lending business, was acquired by PayPal in 2018. Among developing countries, other than the bigtechs in China, the payment fintechs offering credit are the e-wallet company Paytm, the mobile-POS companies Mswipe and PineLab in India, KopoKopo in Kenya, which lends to merchants accepting payments through Lipa na M-Pesa, and iKhokha in South Africa. Given that lending is becoming an important part of the business models of the fintech payment companies across the globe, studying this phenomenon is an interesting avenue for researchers.

Third, payments and credit share an economically organic relationship that fintech helps to harness better as payments have increasingly become electronic. Electronic payments, in contrast to cash payments, have the feature that they leave *digital footprints* that can be tracked. This aspect of electronics payments makes them a natural source of financial data about MSMEs that have no proper financial accounts of their business. This information helps the lender to screen potential borrowers and avoid the pitfalls of adverse selection.

That payments and lending have a close economic connection is not a recent idea. It goes back to the *checking account hypothesis* that is associated with Black (1975), Fama (1985) and Nakamura (1993). The hypothesis states that bank transaction accounts contain useful information about the financial health of the borrowers. Therefore, banks could use that information to screen and monitor the borrowers and take timely actions to mitigate loan losses. Recent studies have empirically found evidence for this hypothesis in different settings. These studies include Puri, Rocholl and Steffen (2017) covering consumer loans in Germany, Norden and Weber (2010) on consumer and firm loans in Germany and Mester, Nakamura and Renault (2007) studying firm loans in Canada. What is new in the wake of fintech innovation is that it has made payment services accessible to MSMEs in the developing countries–with emphasis on the *micro* part of MSME and on *developing*–thus, creating a possibility of generating economically valuable data points for the lenders for the first time.

MSMEs, especially in developing countries, typically transacted in cash and relied less

on electronic transactions. Following a recent boost to financial inclusion and digitization, MSMEs increasingly deal in non-cash-based payments instruments. Cash, however, is still a dominant form of payment in the developing world. India, where our payment company comes from, became a fertile ground for the growth of payment fintech after the government of India demonetized the two largest rupee bills overnight on November 08, 2016.[5] The gradual replacement of the old bills – that accounted for 86% of the currency in circulation – resulted in a shortage of cash in the following months. Crouzet, Gupta and Mezzanotti (2019) find that the demonetization shock led to a persistent increase in electronic payments, though the degree of persistence depends on the pre-demonetization level of adoption of technology.[6]

Another part of the organic relationship between electronic payments and credit is that the relationship allows the payment processor to acquire seniority in the electronic sales of the borrower. Given that any digital payment directed at a merchant that is processed through a payment company's POS will be received by the company first, the company can deduct a fraction of the transaction amount towards debt repayment before settling the remaining transaction amount with the merchant. This is, indeed, the usual repayment practice adopted by the major payment fintech companies.[7] Sales-linked repayment could prove to be especially effective in contexts where loan contract enforcement through traditional channels is costly–for example, in MSME lending and in economies with poor enforcement institutions. Our paper focuses on this potential enforcement advantage gained by payment companies.[8]

Debt contract enforcement is woefully inefficient all over the world but especially so in developing countries (Djankov et al., 2008). Figure A2 in Appendix A presents the number of days to enforce a payment for unpaid debt in different countries and also averages for different

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[5]For a detailed account of the demonetization event and its effects on the Indian economy, see Chodorow-Reich et al. (2020) and Lahiri (2020).

[6]One metric to assess the relative importance of cash versus digital payments is how much debit and credit cards are used to withdraw cash at ATMs compared to their use at POS terminals. Figure A1 in Appendix A shows that in terms of the value of transactions, credit and debit card use at POS terminals is about 36% of their use for ATM withdrawal, significantly up from 12% six years ago. In terms of the number of transactions, this ratio was 63% in the financial year 2018-19, up from 16% in 2012-13. According to the payment data released by the Reserve Bank of India, card payments processed through POS machines have been growing exponentially at a rate of more than 30% per annum and currently are about seven times as high as payments processed through mobile wallets. This rate is fast catching up to global trends. The general picture is that even though India remains a cash-dominant economy, its digital payments are rapidly catching up (RBI, 2020).

[7]For example, for PayPal's loan repayment policy, see `https://www.paypal.com/workingcapital/`; for Square's policy, see `https://squareup.com/us/en/capital`.

[8]In a more traditional lending market, generating *seniority* by linking transactions with repayment has been experimented with under the name of *asset-based lending* . Asset-based lenders typically lend by collateralizing the borrowing firm's accounts receivable. The asset-based lender then gets access to a specially created account in a bank where the borrower is expected to receive all their receivables. However, it is readily inferred that this mechanism is costly because it requires, first, an assessment of the value of the receivables pledged as collateral and then setting up a special account (Mester, Nakamura and Renault, 2007; Berger and Udell, 2006). In the case of payment company lending, this repayment design is nearly costless as it does not require any additional infrastructure other than what already exists for their core payment business.

income groups based on data from Djankov, McLiesh and Shleifer (2007). The figure shows that developing countries like India (425 days) and Brazil (566 days) take a long time to resolve debt payment issues. Even among developed countries, the United States (250 days) and Germany (184 days) are quite slow in enforcing unpaid debt payment, compared to countries like Japan (60 days). Inefficient and slow debt enforcement has a significant impact on the credit market structure and outcomes. When enforcement is costly (in monetary or time units), the borrower may default *voluntarily*, anticipating that the lender would not resort to formal measures of enforcement.[9] Jappelli, Pagano and Bianco (2005), using the variation in the enforceability of contracts across Italian regions, captured by delays and backlogs in trials, establish that lower enforceability of debt contract is associated with lower availability of credit. In terms of contract features, studies have found that better enforceability of contracts is associated with higher loan size, longer loan maturity, lower cost of debt, lower reliance on trade credit, lower reliance on short-term debt and a lower number of credit relationships for the borrowers (Bae and Goyal, 2009; Gopalan, Mukherjee and Singh, 2016; Lilienfeld-Toal, Mookherjee and Visaria, 2012; Qian and Strahan, 2007).

To be sure, the fintech lender's seniority in the revenue stream is not the only substitute for court enforcement. Incentives to strategically default by the borrower could be mitigated by concerns of loss in reputation or social sanctions. One somewhat amusing example of such debt enforcement is the *cobrador del frac*–the debt collectors in tailcoats and top hats–in Spain. These debt collectors try to enforce debt repayment from the willful defaulters by shaming them publicly simply by appearing at the defaulter's doorstep in their flamboyant dress carrying a black briefcase with "debt collector" printed on it.[10] In micro-finance as well, social sanctions and reputation are usually the forces that are effective (Ghatak and Guinnane, 1999). This mechanism, however, may be weakened in urban centers, especially when the lender is not located in the same area.[11]

Another countervailing incentive against strategic default is the lender's threat to cut future funding to the borrower (Bolton and Scharfstein, 1990; Ghosh and Ray, 2016; Hoff and Stiglitz, 1998). However, as noted by Hoff and Stiglitz (1998), and in the spirit of Shapiro and Stiglitz (1984), this countervailing incentive could be weakened if the market for loans is competitive. If a borrower has many financing options, their reliance on one lender is smaller, and the borrower may default on one loan in the hope that they can access loans in the future from other lenders. Thus, the presence of an additional lender in the market creates an *enforcement externality* on other lenders.

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[9]See Ghosh, Mookherjee and Ray (2000) for an overview of theories relating limited enforcement and credit rationing and Visaria (2009) and Gao et al. (2016) for empirical evidence connecting enforceability and defaults.

[10]See `https://www.theguardian.com/business/2013/aug/09/spain-debt-collectors-cobrador-del-frac` (accessed on August 03, 2020).

[11]Other substitutes that are used to a limited extent, for obvious reasons, are collateral and third-party guarantees (Menkhoff, Neuberger and Rungruxsirivorn, 2012).

McIntosh, De Janvry and Sadoulet (2005) test the predictions of Hoff and Stiglitz (1998) in a setting with group-liability microfinance lending in Uganda. They study the impact of competition by group-level changes in repayment rates and other outcomes subsequent to the entry of a competitor lender. They find as groups acquired more choices with the higher number of lenders, their repayment rates fell, although the groups did not drop out of the lender's clientele. We contribute to this literature as well, by comparing the behavior of the borrowers who have better access to the credit market outside of their credit relationship with the payment company than to those who do not. The novelty of our paper is that in addition to delaying rates in repayments, we can study the default behavior of the borrower with better outside opportunities, as we observe defaults in individual loans that are not possible to observe in a group-liability loan. Second, we can actually associate the act of delay and default to strategic behavior because we can study discontinuity in the merchants' sales, and that informs us whether a borrower is manipulating sales. McIntosh, De Janvry and Sadoulet (2005) cannot attribute changes in the repayment rates to strategic behavior of the groups.

Another strand of literature relates competition and relationship lending through a lender's ability to cross-subsidize the borrower inter-temporally. This literature suggests that the lender's monopoly power allows it to support an MSME as it can compensate itself for that support by charging a higher interest in the future. Increasing competition weakens the ability of the lender to charge a higher interest at a future date and therefore reduces the funding for MSMEs (Petersen and Rajan, 1994, 1995). Consistent with this view, Petersen and Rajan (1994) find that credit availability for MSMEs was higher in more concentrated banking markets in the United States. In contrast to this theory, the enforcement theories link the availability of credit with competition through the opportunistic behavior of the borrowers when facing a competitive credit market. While we do not empirically test the availability of credit and competition, we do establish the existence of opportunistic behavior among defaulting borrowers who have better access to the credit market.

One way to mitigate the adverse consequences of enforcement externalities could be a system of fast and accurate transmission of information on credit performance to all the lenders in the market. However, it is a challenge to set-up a credit reporting system that comprehensively covers MSMEs. In the country of our study, India, credit information sharing is far from perfect. There is no public credit registry. With several private bureaus and public agencies collecting credit information in different markets, the system of credit information collection is quite fragmented. Further, loans made through non-bank financial companies (NBFCs) in India are not comprehensively covered in any system (RBI, 2018). Further, the practitioners we spoke to informed us that for the unsecured credit, the gaps in credit information are larger. Even in countries such as the United States, it is difficult to get a complete picture of the MSMEs through credit scores. A recent report on small businesses finds that about 88% of small businesses in the United States use the business owner's credit scores in some form to obtain credit while 40% use the owner's credit score exclusively to obtain credit (Federal Reserve, 2020).

A payment company lender may still be able to avoid the negative consequences of enforcement externality. Although the availability of multiple sources of finance in the presence of a weak credit reporting system heightens the *willingness to default*, the payment company intermediated lending reduces the *ability to default*. The extent to which the fintech payment companies can substitute for institutional enforcement depends on the extent to which the merchants are forced to route their payments through the company's POS. Given that their credit behavior is not reported to the credit bureaus, the borrowing merchants might tinker with the loan repayment if they could control the extent to which electronic payments happen through the lending company's system. We study precisely this, using a cash crunch episode that occurred in Mid-March and April 2018 in a few Indian districts. The shortage of cash during that episode allows us to study the counterfactual outcome if such control by the borrower over their electronic sales is diminished.

3 Institutional set-up

There are several similarities in fintech payment company lending across different countries. Payment companies collaborate with licensed lenders to make loans, as most do not have a banking license themselves.[12] At the time of making the loans that are part of this study, our payment company, in India, had agreements with a number of lending companies that are non-bank financial companies (NBFCs).[13] However, one NBFC dominated the loan portfolio, extending more than 80% of all the loans. All other lenders, individually accounting for a small share of the loan portfolio, had made non-standardized, large-ticket-size loans to select borrowers. We work with loans made by the largest lender. All the loans, like any typical payment company loan, were unsecured.

Figure 1 presents an example of a typical loan intermediated through a payment company in comparison to traditional loans. In a traditional set-up, depicted in Figure 1a, the lender (say, a bank or NBFC) gives the loan to the borrowing merchant directly. The loan is amortized over the course of the tenure of the loan, through payments made by the borrower to the lender, usually of a fixed amount and at fixed intervals (weekly or monthly frequency). So, a typical uncollateralized bank loan is characterized by tenure and a repayment schedule outlining an amount and a frequency of repayment based on the amortization rule. In this case, the lender only cares if the borrowing merchant is current on the repayment schedule and does not observe the revenue flow of the borrowing merchant. Also, the lender does not have control of whether the borrower uses the sales revenue to meet expenses first before paying towards loan

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[12]For instance, PayPal's lending partner is WebBank and Square's lending partner, so far, is the Celtic Bank in Utah, in the United States.

[13]NBFCs are financing companies that do not have a deposit franchise, barring a few that were allowed to collect *non-demandable* deposits before 1997. The Reserve Bank of India has not given a deposit franchise to any non-bank financial company since 1997. NBFCs are also not part of the payment and settlement system. NBFCs are regulated and supervised by the Reserve Bank of India.

amortization.

Figure 1: An Example of a Typical Lending Process Under Payments Company Loan Program

(a) Traditional lending   (b) Payment company lending
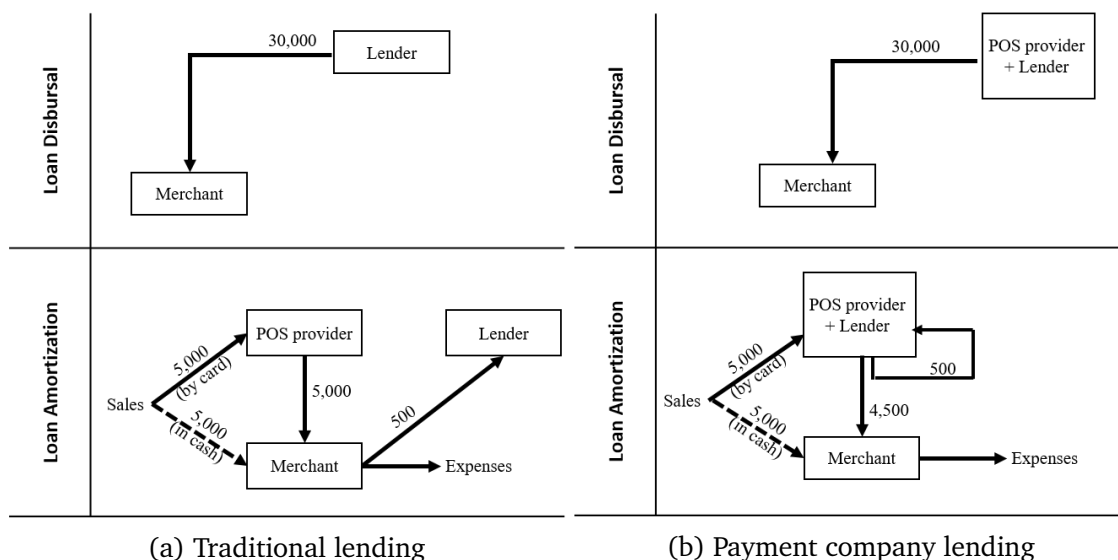
Example of a loan with a principal amount of INR 30,000. Loan, as in a typical payment company loan, is unsecured. Neither lender nor the payment company can observe cash revenue (depicted as dotted line) of the merchant. Payment company processes electronic (e.g. card) payments for the merchant. Bottom panels show repayment of one *instalment* (out of possibly many) towards loan amortization under two different lending arrangements. In the case of POS lending, the repayment is a fixed proportion (here 10%) of each card transaction processed through the payment company. Note the figure abstracts from many real life details – for instance, it does not take into account processing fees charged by the payment company on each transaction it processes.

Figure 1b depicts a typical lending program where the loan disbursal and collection is managed through the payment company. The payment company screens the borrowers as it observes the electronic portion of the firms' revenue streams. The company provides information on the potential borrowers and their sales-related statistics to the lending NBFC, which then decides whether to make an offer and the loan amount. Once the lender approves a loan, the payment company makes a loan offer to the merchant outlining the loan amount (principal), interest rate and a *suggested tenure* (more details about the loan terms are discussed later). Once the merchant accepts the offer, the lender disburses the loan, sometimes after some additional checks.

In contrast to traditional bank lending, under POS lending, the loan is amortized by deducting a fixed percentage from each electronic transaction processed by the company for the borrowing merchant. Thus, these loans provide an inherent flexibility to merchants in their repayment, as merchants do not need to repay in a period when there are no sales. They can make up for lower repayments on the days when the sales are higher. Repayment flexibility that

gives the borrower a way to reschedule repayments is found to have positive effects on business investments and profitability and is associated with lower defaults rate if the borrowers have financial discipline (Barboni and Agarwal, 2018).[14]

These kinds of data-driven flexible loan repayment schemes are being adopted in other areas as well. For example, Germany's second-largest bank, Commerzbank, launched "pay-per-use loans" where the repayment on loans for a manufacturing firm depends on the usage rate of the machines in the firm.[15] The pay-per-use model is seen as a promising innovation also in the machinery leasing business, facilitated by the "Internet of Things" that allows measuring the usage of leased products (Oliver Wyman, 2019).

The additional advantage of amortization linked to sales is that despite being flexible, it creates a *seniority* for the lender in the revenue stream of the borrowing merchant. As depicted in Figure 1, under a traditional credit relationship, a borrowing merchant's repayment to the lender and its sales settlement with the payment company are not linked. Therefore, the borrowing merchant has more discretion over how to split their revenue over expenses and loan amortization. Under POS lending, the merchant does not enjoy that discretion as the payment company already deducts a proportion of card sales towards loan repayment while processing the card transactions. The payment company then remits the lender from the collected repayment amount according to their own revenue-sharing agreement. In this paper, we treat the payment company and lender as one entity as our focus is on the interaction between the borrower on one side and the payment company plus the lender on the other.

The loan amount is set by the lender based on their internal model and considers, among other things, the value of transactions in the past months. Each loan has a two percent per month interest charge, which is about the standard rate charged in NBFC lending to risky borrowers in India and is in the range of interest rates charged by fintech lenders in the consumer credit market in the US and the UK (Cornelli et al., 2020). Most loans have a *suggested* tenure of 90 days. The lender introduced 180-day suggested tenure loans from August 2018 on. The lender decided which tenure to suggest to which borrower. Our data indicate that most 90-day loans to the first time borrowers while most 180-day loans went to repeat borrowers, after the introduction of the latter. The tenures were only suggested as the loans were sales linked, and there was no penalty for late payment or for carrying forward the loan beyond its *suggested due date*.[16]

The deduction rate was set at ten percent, i.e., ten percent of each sale processed through

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[14]Also see Field et al. (2013) and Field and Pande (2008) for discussion about repayment flexibilities relating to a delayed start in repayment and repayment frequency, respectively, under traditional microfinance lending.

[15]https://www.commerzbank.de/en/hauptnavigation/presse/pressemitteilungen/archiv1/2018/quartal_18_02/presse_archiv_detail_18_02_75466.html

[16]For this reason, we define another concept of loan tenure for this study that we call *implied tenure*–the number of days the borrower should take to repay the loan if post-disbursal sales are the same as the long-term average sales pre-disbursal. We determine the delay in a loan repayment using this concept of tenure. See Section 4 for more discussion.

the payment company would go towards the repayment. The merchant receives the remaining 90% of the sales minus any other charges, such as transaction fee for certain kind of transactions, if levied by the payment company. However, merchants also had the option of repaying the loan through direct transfers and closing the loan at any time, without any additional charges. Sometimes, the merchants could also change the deduction rate from ten percent to a higher number–although merchants used this option rather rarely.[17]

The payment company/lender has not shared its internal screening criteria with us. However, it informed us that it based its credit decisions solely on the past transaction data. Specifically, the lender acquired but did not use credit scores at the time of making loan decisions for its lending program in 2017 and 2018. In fact, the lender's reliance only on the past sales data is not an aberration. Both the United States-based payment fintech lenders, Paypal and Square, also do not use credit scores to make lending decisions.[18] The lender acquired credit scores from one of the largest credit bureaus in India–TransUnion CIBIL. The credit scores are the personal credit scores of the owners of the borrowing MSME.

Figure 2 plots the distribution of credit scores of the borrowing merchants whose credit history existed at the time of borrowing. It also plots, as a benchmark, the distribution of scores that TransUnion CIBIL publishes (TransUnion CIBIL, 2017). The benchmark considers any type of loan, including secured and unsecured loans, loans of any maturity, any loan size and loans disbursed by any reporting institution. Because banks dominate the market for credit, we can think of the benchmark distribution as the distribution of scores among bank borrowers.

The figure suggests that the fintech payment company mainly serves borrowers with low credit scores who are unlikely to have access to credit from banks. For instance, the median credit score for payment company loans is about 730, while for bank loans, it is above 800. Further, according to CIBIL, credit scores above 700 are considered good by the credit market.[19] Among the borrowers with credit scores, the fintech payment company made one in three loans to borrowers with a score below 700. For banks, this number was about one in 10. Further, about 10% of the loans by the payment company went to those borrowers who did not have any credit history (no credit score). We also conjecture that majority of bank loans to low-scored loans are secured loans. The fintech payment company, on the other hand, makes unsecured

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[17]Some features of this contract are similar to the ones offered by U.S. payment companies. PayPal also does not have a fixed loan tenure, but some minimum repayment needs to be maintained over a period of time. Square has a suggested tenure of 18 months without any late fees but has the authority to debit the Square-linked bank account of the borrower in case of delay. Neither company applies monthly interest charges but instead charges a fixed fee that does not depend on the time taken for complete repayment. Both companies also allow early repayment outside of the transaction processing channel. Both companies offer varying deduction rates to different borrowers depending on the loan amount and sales history.

[18]For PayPal's statement about credit scores, see `https://www.paypal.com/workingcapital/faq` and for Square's, see `https://squareup.com/help/us/en/article/6531-your-credit-score-and-square-capital-faqs`. Accessed on December 19, 2020.

[19]See `https://www.cibil.com/faq/understand-your-credit-score-and-report`(Accessed on December 20, 2020).

Figure 2: Distribution of Borrower Credit Scores: Payments Company Versus Benchmark
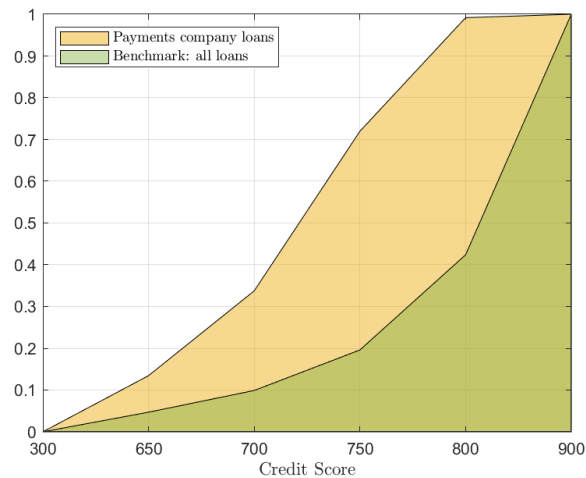

Figure plots the distribution of credit scores of the merchants (business owners) who borrowed from the payments company. For comparison, a benchmark distribution of scores for all the borrowers (taking any type of loan: unsecured, secured, any maturity and so on) as reported by the credit bureau TransUnion CIBIL, is also plotted. The benchmark distribution may be understood as a distribution of credit scores for bank loans. Credit score ranges between 300 and 900, with higher score representing better credit quality. Credit scores above 700 are considered good.

loans to all, including low-scored borrowers. These statistics not only inform us about the clientele of the payment company but also provide evidence that supports the lender's claim that it did not use credit scores in loan decisions.[20]

In addition, perhaps because of their unconventional and flexible repayment schedule, payment companies do not report loan performance to credit bureaus.[21] This set-up provides us with a unique opportunity to link borrowers' outside opportunities with their loan performance. We believe borrowers who had a credit score above the threshold of 700 had better outside opportunities because they would be assessed favorably by the credit market. The low-score borrowers on the other hand will have fewer opportunities to borrow outside of their credit relationship with the payment company. We link the outside opportunities of the borrowers with their sales manipulation behavior.

4   Data and Empirical Strategy

4.1   Data

We obtain confidential, anonymous loan-level and transaction-level data from a payment company that is a major player in the Indian electronic payment ecosystem. The company is a

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[20]See the next section for summary statistics and Section 5.3 for more discussion on credit scores.

[21]See footnote 18 for links to the credit reporting policies of Square and PayPal.

provider of mobile-POS machines mainly to MSMEs. The loan data provides, for each loan, the principal (*loan amount*), date of loan disbursal, interest rate, suggested tenure, date when the loan was fully repaid (*loan closure date*), and shortfall in the repaid amount compared to the amount owed, if any. We use the data on shortfall to identify loans that went into default.

The company started its lending program in the middle of 2017. In the beginning, when the lending program was in the pilot phase, the company experimented with different kinds of loan policies before settling on a set of standard contract terms described in the previous section. We, therefore, omit the data from the initial few months of the loan program and include loans from October 2017 onward in our study. Within the standardized contracts, the company offered a suggested tenure of 90 days for 81% of the loans and introduced 180-day suggested tenure loans in August 2018 that accounted for the remaining 19% of the loans. We include both types of loans in our analysis.

We have also obtained anonymized transaction (card swipe) level data for approximately 270,000 merchants over the period from January 2015 to February 2019. This dataset contains details for each transaction, the transaction amount, transaction date, and card type (but not card number). We also obtain demographic information like industry and zip code (called *PIN* in India) for each merchant. In total, we observe details for more than 99.4 million transactions. Using unique identifiers for each merchant, we can map the loan information for borrowing merchants from the loan data to their sales from the transaction data. We also use transaction data for non-borrowing merchants for certain exercises. Because our transaction data end at the end of February 2019 and we want to track the transaction activity of the borrowers for up to three months after the loan disbursal, we restrict our analysis to loans made up to the end of November 2018.

We also obtain the anonymized historical credit bureau information from the lending partner of the payment company and map it with our loan and transaction data. The lender had not used the credit information for the loans made in 2017 and 2018 but had acquired them regardless. The credit scores are those of the owners of the businesses that received loans. The lender had sourced the credit information data from TransUnion CIBIL. The credit bureau data includes credit scores (also called *CIBIL score*) of the borrowers at the time of loan disbursal. The CIBIL credit score ranges between 300 and 900, with higher scores indicating better credit quality of the borrower and scores above 700 considered to be good in the credit market. CIBIL score data also identifies the borrowers who did not have a sufficiently long recent history to be assigned a score. We call these loans *unscored loans*. We could not map about 18% of the loans in our dataset with the bureau data from the lender. For this reason, the sample size for analysis relating to credit scores is smaller than our overall sample. Out of the 82% of the loans that could be mapped, about 10% loans were unscored.

A final consideration for our study sample is that we are careful not to include those loans of the repeat borrowers in the analysis that were closed in proximity to the disbursal of their next loan. The reason is that because of the sales-linked repayment, loans tend to close on

the days with extraordinary high sales. This means for the borrowers who took more than one loan (*repeat borrowers*), due to this closure-day effect, data will show an unusually high sales pre-disbursal on their next loan. It might also artificially heighten any discontinuity on these repeat loans. Therefore, in all the analysis, we consider only those repeat loans that were disbursed a certain amount of time after the closure of a previous loan. For instance, if we analyze sales in a seven-day window around disbursal, we consider only those repeat loans in the sample that were disbursed at least eight days after the closure of a previous loan by the same borrower (in short, the *closure gap* is at least eight days). Thus, our sample changes in accordance with the window we choose for our analysis. Therefore, our robustness checks for alternative windows are also robustness checks on whether our results hold for different samples. We use a seven-day window around disbursal for all the baseline regressions and figures. Therefore, we present all our summary statistics in the following subsection after excluding the repeat loans that had a closure gap of fewer than eight days. For more discussion on this topic, see Section 4.3.

4.2 Summary Statistics

Tables 1 through 3 provide summary statistics on several loan-related variables. Table 1 covers all borrowers and all loans. Table 2 looks at the sub-sample with only one-time loan takers (*non-repeat borrowers*) and Table 3 considers repeat borrowers and their first loan as well as their second and subsequent loans (*repeat loans*) in its two sub-tables.[22]

The average loan made by the payment company is about INR 38,000, roughly about USD 570 in the nominal exchange rate or roughly about USD 1,900 in purchasing power parity exchange rate. The average loan size for a borrower increases on subsequent loans. The interest rate charged on all loans is 2% per month, regardless of whether it is a first or repeat loan. This appears to be a standard practice in other countries, too. In a seminal study, Petersen and Rajan (1994) find that for the small businesses in the United States, the benefit of the relationship accrues to the borrower through quantity and not price channels. As discussed earlier, all the loans had a *suggested* tenure of 90 days or 180 days, i.e., they were *recommended* to be paid back in those many days; going beyond suggested tenure did not entail any penalty or late fees, but only interest charges that would accrue monthly.

Because the deduction rate was fixed at 10% for all borrowers, it does not immediately follow that merchants would be able to repay the loans within the suggested number of days with their *normal* sales. Merchants who have high average sales relative to repayment amount (principal + interest) would repay earlier than the end of the suggested maturity, while the merchants with lower relative sales might take longer than the suggested maturity, unless, after borrowing, they increase their sales above their average sales. Indeed, the suggested nature of

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[22]Table A2 in the Appendix presents summary statistics for loans according to month of disbursal of the loans.

tenure was part of the flexibility offered to the borrowers. Thus, classifying a loan as delayed would give an incorrect picture if, in the normal course of business, the loan should have been repaid in, for instance, 120 days instead of the recommended 90 days. Similarly, a merchant with very high sales who, in the normal course should have repaid the loan in 40 days and takes 80 should be regarded as late, but by the suggested 90-day tenure criterion, such a merchant will be classified as not delayed. Therefore, if we require a measure to capture whether a loan was delayed and by how much, we need a measure of tenure that is linked to the average past sales of the borrowing merchant. For this reason, we define an additional measure of tenure that we call *implied tenure*. Implied tenure is the number of days that would be required to repay the loan (loan amount and interest over the suggested tenure, at a 10% deduction rate) if the merchant continued to have same sales as their long-term average sales before disbursal (pre-disbursal long-term average). More precisely,

$$\text{implied tenure} = \frac{\text{loan amount} + \text{interest amount over suggested tenure}}{0.1 * \text{average long-term sales pre-disbursal}}$$

We define long-term average sales as the per-day average calculated over the 90-day window consisting of sales in 30 days to 119 days *before* disbursal. We do not include the days close to the disbursal date in average sales calculations because some short-term, unusually high sales days that increase the probability of getting a loan might overstate the actual health of the borrowers. Note that this measure, too, is not free from problems. It underestimates implied tenure by including in the repayment amount the interest for suggested tenure only when the loan could have taken longer to repay and incurred a higher interest amount. Similarly, it over-estimates tenure for loans where the merchant has high sales and could finish repaying the loan, for instance, in one month and would not have been required to pay interest for the full suggested tenure. Despite the caveats of over- and under-estimation, we subjectively judge these inaccuracies in the measure as a minor issue and deem our measure of implied maturity as the most practical approach to account for the implicit contractual flexibility of the loan tenure.

Table 1 shows as against the mean suggestive tenure of 106 days, a typical loan had an implied tenure of about 142 days. Within that, loans with 90-day suggested tenure had an average implied tenure of 131 days and for 180-day suggested-tenure loans the mean implied tenure was 188 days. Table 3 shows implied tenure increased with subsequent loans suggesting that merchants got bigger size loans in relation to their average sales over subsequent loans. Longer loan tenure on repeat loans is one of the ways lenders reward their long-existing borrowers

We receive an update of the lender's *loan-book* as on 31 December 2019—thirteen months after the disbursal of the last loan included in our analysis. This update was a snapshot review of the asset quality (loan performances) in the long-run and helps us classify all the loans into the performing and non-performing categories. Non-performing loans comprise of *late* and

default loans. Performing loans are those that are not classified as non-performing (that is, neither late nor default). Late loans are those where the borrowers fully paid back but took at least 31 days longer than the implied tenure to do so. We define default loans as those loans that had a "large" shortfall (pending amount) as on 31 December 2019. We call a shortfall large if it is more than five percent of the due repayment amount as on 31 December 2019.[23] With this criteria, out of 9,327 loans in our sample, we classify about 19% as late, about 12% as default and the remaining 69% as performing loans (Table 1). For a quick reference, we summarize the sample definitions in Table A1 in Appendix A.

We believe the label *default* is appropriate for the loans with large shortfalls for the following reasons. First, the average shortfall as a proportion of repayment due, for the default loans pending as on the update date was huge—about 66%. Further, 90% of these pending-default loans had a shortfall of more than 30% as on 31 Dec 2019. Therefore, these loans represented large losses at the time of the review. Second, the review (and shortfall calculation) was on 31 Dec 2019, which was 13 months after the disbursal of the last loan in our analysis and seven months after the *latest* suggested due date. Admittedly, the due date was only suggested, but merchants were encouraged to follow that with the intention to make the merchants with low sales to transact more using the payment company's POS, after taking the loan. Further, all except 42 pending-default loans had *implied due date* before 31 Dec 2019. Technically, these 42 loans could still repay "on time" yet we labelled them as default because they carried excessive shortfall that the chances of on-time payment were bleak. For instance, only 10 out of 42 of these loans had a shortfall below 50%. Finally, we do recognize that asset review is a dynamic process and some of the pending-default loans may eventually be fully paid up. However, as discussed above, such loans would still fall into the late category. Therefore, these future changes will only result in compositional shifts between default and late sub-categories and will leave the set of non-performing loans unchanged. For this reason, we present all our results for the non-performing loans before drilling into its sub-categories.

Of the 7,659 loans for which we could map the loan and credit scores data, we find that 10% of these loans went to borrowers without any credit history. This proportion is roughly the same across non-repeat and repeat loans. The fact that a sizeable proportion of the payment company's clientele has no credit history suggests that fintech lenders are able to use other economically relevant variables for credit assessment as a substitute for the credit history. Indeed, as discussed above, the lender in our study did not rely on credit scores at all to make loan decisions. This fact is also reflected in the observation that the distribution of credit scores hardly varies over different samples in Tables 1 through 3. Table A3 presents summary statistics over credit scores, dividing the population into those with a favorable credit score (above 700), an unfavorable credit score (below 700) and those with no credit history. .

To study transaction behavior at the merchant level, we aggregate the swipe level data for

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[23]A small proportion of the default loans were closed by the lender even with a large shortfall. These closed loans were basically written-off by the lender. Majority of default loans were still being pursued.

Table 1: Summary Statistics on Loans:All Borrowers

	No. Loans	Mean	Median	SD	p10	p90
Loan amount (INR1,000)[a]	9,327	38.07	25.00	38.39	10.00	83.00
Relationship length (months)	9,327	14.68	13.57	8.58	4.40	26.71
Suggested tenure (days)	9,327	106.90	90.00	35.15	90.00	180.00
Implied tenure (days)	9,327	141.97	110.18	171.50	55.35	229.86
Credit history exists (1 = Yes)	7,659	0.90	1.00	0.30	0.00	1.00
Credit score	6,886	713.88	727.00	53.63	639.00	773.00
Days past due (days)[b]	8,246	10.03	2.00	61.84	-54.00	79.00
Implied days past due (days)[b]	8,246	-17.69	-3.16	128.70	-93.77	59.40
Late (1 = Yes)	9,327	0.19	0.00	0.39	0.00	1.00
Default (1 = Yes)	9,327	0.12	0.00	0.32	0.00	1.00
Non-performing (1 = Yes)	9,327	0.31	0.00	0.46	0.00	1.00

[a] INR 1,000 corresponds to approximately USD (PPP) 50, or approximately USD 15, as per 2017–2018 exchange rate series available on OECD.

[b] Among non-defaulting loans.

p10 and p90 refer to the 10th and 90th percentile respectively. Loan amount is the principal amount. Relationship length is the number of months between the first ever transaction by the borrowing merchant with the payments company and the loan disbursal date. All loans had suggested tenure of either 90 days or 180 days. Implied tenure is calculated taking into account historical average transaction value of the merchant and the total amount owed (loan amount incl. interest). Given the 10% deduction rate and their average past transaction value, it calculates how many days a borrower would take to repay the loan. *Credit history exists* is a dummy that takes value 1, if the credit bureau assigns a credit score. Credit scores range between 300 and 900, with higher scores indicating better borrower quality. For loans for which the bureau indicated that no recent credit history existed at the time of the borrowing, the dummy *Credit history exists* assigns a 0. *Days past due* is the difference between loan closure date and suggested due date (= disbursal date + suggested tenure). *Implied days past due* is calculated as the difference between the loan closure date and the implied due date (= date of disbursal + implied tenure). *Late* is a binary variable that takes value 1, if a loan was non-defaulting and was repaid at least 30 days beyond the implied due date. *Default* is a binary variable that takes value 1, if shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. *Non-performing* takes value 1 when either the loan is in default or is late. Loans were made between October 2017 and November 2018. All the repeat loans included in the sample were disbursed at least eight days after the closure of the preceding loan of the same borrower. For more details on the variables see Table A1 in the appendix.

Table 2: Summary Statistics on Loans:Non-repeat Borrowers

	No. Loans	Mean	Median	SD	p10	p90
Loan amount (INR 1,000)[a]	2,152	38.51	22.00	42.65	9.00	94.00
Relationship length (months)	2,152	12.69	11.22	8.25	3.84	23.01
Suggested tenure (days)	2,152	91.00	90.00	9.45	90.00	90.00
Implied tenure (days)	2,152	118.77	101.06	168.96	55.86	176.44
Credit history exists (1 = Yes)	1,711	0.90	1.00	0.30	0.00	1.00
Credit score	1535	717.86	730.00	53.69	641.00	775.00
Days past due (days)[b]	1,578	30.62	10.00	67.77	-31.00	119.70
Implied days past due (days)[b]	1,578	9.93	4.09	92.56	-59.75	103.10
Late (1 = Yes)	2,152	0.22	0.00	0.41	0.00	1.00
Default (1 = Yes)	2,152	0.27	0.00	0.44	0.00	1.00
Non-performing (1 = Yes)	2,152	0.48	0.00	0.50	0.00	1.00

[a] INR 1,000 corresponds to approximately USD (PPP) 50, or approximately USD 15, as per 2017–2018 exchange rate series available on OECD.
[b] Among non-defaulting loans.
 Non-repeat borrowers are those that took only one loan in the period until February 2019. See Table 1 for notes and for more details on the variables see Table A1 in the appendix.

each calendar day for each merchant. Table 5 presents summary statistics on transaction-related variables for the borrowing merchants. These statistics are mean values per-day-per-merchant calculated over different windows. We also normalize the transaction variables for each merchant by their *pre-disbursal long-term* averages. The *pre-disbursal long-term* averages are calculated in the same way as we calculate the long-term averages when computing the implied tenure: the average per day calculated over the 90-day window spanning 119 to 30 days before disbursal.

The 180-day window captures the mean in the window spanning 90 days before disbursal to 90 days after disbursal, including the day of disbursal. The second and the third rows of Table 5 look at the very short window pre- and post-disbursal, respectively. We also calculate *pre-disbursal short-term* averages in the 90-day period spanning 90 days to 1 day before disbursal, with the idea to capture sales trends immediately prior to the disbursal but over 90 days. *Post disbursal* period averages are calculated over a 90-day period between day 0 and day 89 after disbursal.

An average borrowing merchant receives about INR 3,980 per day through electronic means from customers. The merchant experiences an uptick in sales before disbursal, as evident from the fact that the merchants' short-term average sales are about 5% higher than their long-term average pre-disbursal. The sales, however, decline in the post-disbursal period. The decline is quite substantial for non-repeat borrowers. This decline is partly due to selection: many non-repeat borrowers are non-repeat because of their poor performance on their loan. Post-disbursal, the average borrower transacts slightly more than its long-term average pre-disbursal. This increase suggests that the lending program, on average, is successful in helping merchants maintain their long-term sales, if not at higher levels. Payment companies offer the lending program not just to earn interest income but also to incentivize merchants to transact more,

Table 3: Summary Statistics on Loans:Repeat Borrowers

	No. Loans	Mean	Median	SD	p10	p90
Loan amount (INR 1,000)[a]	3,207	30.36	20.00	31.76	8.00	64.00
Relationship length (months)	3,207	12.30	10.74	8.10	3.75	22.97
Suggested tenure (days)	3,207	90.14	90.00	3.55	90.00	90.00
Implied tenure (days)	3,207	102.15	95.18	66.33	47.77	156.71
Credit history exists (1 = Yes)	2,626	0.89	1.00	0.32	0.00	1.00
Credit score	2,329	712.07	724.00	54.41	636.00	772.00
Days past due (days)[b]	3,207	6.18	2.00	33.47	-35.00	51.00
Implied days past due (days)[b]	3,207	-5.82	-0.06	67.24	-60.37	47.78
Late (1 = Yes)	3,207	0.19	0.00	0.39	0.00	1.00
Default (1 = Yes)	3,207	0.00	0.00	0.00	0.00	0.00
Non-performing (1 = Yes)	3,207	0.19	0.00	0.39	0.00	1.00

(a) 1st Loan

	No. Loans	Mean	Median	SD	p10	p90
Loan amount (INR 1,000)[a]	3,968	44.07	30.00	39.74	14.00	93.00
Relationship length (months)	3,968	17.68	16.39	8.22	8.05	29.90
Suggested tenure (days)	3,968	129.06	90.00	44.61	90.00	180.00
Implied tenure (days)	3,968	186.74	141.65	215.72	63.86	314.76
Credit history exists (1 = Yes)	3,322	0.91	1.00	0.29	1.00	1.00
Credit score	3,022	713.25	727.00	52.90	639.00	771.00
Days past due (days)[b]	3,461	4.20	-1.00	75.76	-85.40	98.00
Implied days past due (days)[b]	3,461	-41.29	-12.27	174.19	-150.58	61.42
Late (1 = Yes)	3,968	0.18	0.00	0.38	0.00	1.00
Default (1 = Yes)	3,968	0.13	0.00	0.33	0.00	1.00
Non-performing (1 = Yes)	3,968	0.31	0.00	0.46	0.00	1.00

(b) Repeat Loan

[a] INR 1,000 corresponds to approximately USD (PPP) 50, or approximately USD 15, as per 2017–2018 exchange rate series available on OECD.
[b] Among non-defaulting loans.
 Repeat borrowers are those that took more than one loan in the period under study. Repeat loan refers to second and subsequent loans of the repeat borrowers. All the repeat loans included in the sample were disbursed at least eight days after the closure of the preceding loan of the same borrower. See Table 1 for notes and for more details on the variables see Table A1 in the appendix.

Table 5: Summary Statistics on Transactions Around Loan Disbursal

Mean values (except number of loans)

	Transactions				Normalized Transactions			
	All	Non-rep.	Repeat Borrowers		All	Non-rep.	Repeat Borrowers	
	Brwrs.	Brwrs.	1st Loan	Rep. Loan	Brwrs.	Brwrs.	1st Loan	Rep. Loan
Transaction value[a]								
180-day window	3.87	4.03	3.83	3.82	1.04	0.92	1.10	1.05
−7 to −1 days	4.04	4.39	3.76	4.08	1.10	1.05	1.11	1.12
0 to 6 days	3.93	4.25	3.80	3.86	1.05	0.95	1.09	1.06
Pre-disbursal long-term	3.98	4.71	3.70	3.82	1.00	1.00	1.00	1.00
Pre-disbursal short-term	4.14	4.79	3.82	4.03	1.06	1.05	1.07	1.06
Post-disbursal	3.61	3.26	3.84	3.61	1.01	0.79	1.14	1.04
Number of transactions								
180-day window	2.77	2.54	3.06	2.66	1.02	0.92	1.08	1.02
−7 to −1 days	2.80	2.69	2.99	2.70	1.04	0.97	1.06	1.06
0 to 6 days	2.80	2.58	3.07	2.70	1.03	0.95	1.07	1.05
Pre-disbursal long-term	2.77	2.82	2.88	2.66	1.00	1.00	1.00	1.00
Pre-disbursal short-term	2.85	2.87	2.99	2.72	1.04	1.02	1.05	1.03
Post-disbursal	2.70	2.22	3.14	2.60	1.00	0.81	1.10	1.01
Number of loans	9,327	2,152	3,207	3,968	9,327	2,152	3,207	3,968

[a] Non-normalized transaction values are in thousand INR. INR 1,000 correspond to approximately USD (PPP) 50, or USD 15, as per 2017–2018 exchange rate series available on OECD.

All values, except for number of loans, are average per day per borrowing merchant calculated over different windows. *180-day window* is centred at the disbursal date and covers 90 days prior and 90 days after disbursal inlcuding the day of disbursal. Day 0 refers to the disbursal date. Days with a minus sign are days prior to disbursal. *Pre-disbursal long-term* period refers to the 90-day period between days -119 and -30. It aims to capture the average sales away from the disbursal date. *Pre-disbursal short-term* period refers to the 90-day period between days -90 and -1 and is considered short term for including days shortly before the disbursal. *Post-disbursal* refers to the 90-day window between day 0 and day 89. We normalize the transaction value and number of transactions by their averages calculated in the *pre-disbursal long-term* period respectively.

as higher sales increase the lender's income from the proportional transaction charges on transactions and also keep the merchant engaged to the lender's network. However, clearly, there are many borrowers on whom the payment company loses money because the borrower reduces sales post-disbursal. Summary statistics over loan status in Table A4 in the Appendix A shows that merchants with *non-performing* loans reduce their sales drastically after disbursal. In what follows, we study the nature of this reduction.

4.3 Empirical Strategy

We study the borrowing merchants' sales behavior around the day of disbursal. More specifically, we want to understand whether merchants discontinuously alter their sales immediately after loan disbursal. The idea is that a discontinuous change in POS sales on the disbursal date indicates a voluntary action of the borrowing merchant to influence sales in response to the disbursal. In particular, given the sales-linked repayment of loans, merchants may divert their electronic sales away from the lender's POS to circumvent automatic repayment and delay or default on their loans. A merchant may divert sales simply to manage short-term liquidity needs and not necessarily with the intention to default. In such a case, we might observe discontinuity for the loans that turn out to be performing.

To measure the discontinuity, we apply the regression discontinuity (RD) approach with the days since disbursal (denoted as "day") as the running variable. For the loan i and transaction date t, days since disbursal is defined as $day_{i,t} := t - disbursal_i$, where $disbursal_i$ is disbursal date for the loan i. This implies $day = 0$ on the disbursal date, $day < 0$ for transactions observed before disbursal, and $day > 0$ for transactions observed after disbursal. Transaction for loan i refers to the transaction of the merchant who is the borrower of loan i. Digital sales-related variables for loan i and observed at time t are denoted as $esales_{i,t}$. For most of our analysis, we use the normalized daily value of transactions as our relevant $esales_{i,t}$ variable. We also use the normalized daily number of transactions for some other specifications.

Our RD design is close to those studies that use *age* as a running variable where treatment (such as access to pension and medical care, etc.) is based on satisfying an age criterion: where, while everyone crossing the age cut-off receives treatment, they are treated at different points in calendar time. Some examples of such studies include Card, Dobkin and Maestas (2008, 2009); Carpenter and Dobkin (2009).[24] In our set-up, loans are disbursed at different points in calendar time with the cut-off, $day = 0$, "determining" the disbursal. Of course, as in the case of *age*-based RD designs, there are legitimate concerns about the influence of anticipation of treatment, and we address them in Section 5.2.

We study discontinuity by running local polynomial regression that fits, in *narrow* bands around the cut-off, a polynomial each on the left and the right of the cut-off, which in our case is the disbursal day ($day = 0$). Then intuitively, discontinuity is reflected in the difference in

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[24]For a list of other *age*-based RD designs, see Lee and Lemieux (2010).

the values the regression functions take at the cut-off, day = 0. We denote the length of the bandwidth as h. More generally, a regression that fits polynomials in a bandwidth of size h uses data on h number of days before disbursal (i.e., left of the cut-off) and h number of days after disbursal, including the day of disbursal (i.e., right of the cut-off). When h is small and only observations very close to the cut-off are included, it is called a *local regression*. We use the terms *bandwidth* and *window* interchangeably.

The idea of comparing the values of two polynomial fits at the cut-off point can be implemented through one regression by including dummy variables for post-disbursal days. More precisely, for a local comparison, we regress, in a window h around the disbursal date, the transaction variable of interest, $\texttt{esales}_{i,t}$, on a polynomial of $\texttt{day}_{i,t}$ allowing for different coefficients, and different polynomial degrees (p,q) before and after loan disbursal. We perform pooled regression:

$$
\min_{\alpha,\tau,\beta_s,\gamma_s} \sum_{i=1}^{n}\sum_{t\in T} \mathbb{1}\{|\texttt{day}_{i,t}| \leq h\}\Bigg[\texttt{esales}_{i,t} - \alpha - \tau \times \mathbb{D}_{i,t}
$$
$$
- \sum_{s=1}^{p}\big(\beta_s \times (1-\mathbb{D}_{i,t}) \times (\texttt{day}_{i,t})^s\big) - \sum_{s=1}^{q}\big(\gamma_s \times \mathbb{D}_{i,t} \times (\texttt{day}_{i,t})^s\big) \Bigg]^2 , \tag{1}
$$

where T is the set of transaction dates. $\mathbb{D}_{i,t} := \mathbb{1}\{\texttt{day}_{i,t} \geq 0\}$ is a dummy variable that is 1 when $\texttt{day}_{i,t} \geq 0$ (post-disbursal), and 0 otherwise. $\mathbb{D}_{i,t} \times (\texttt{day}_{i,t})^s$ is the interaction term between $\mathbb{D}_{i,t}$ and the sth polynomial term of $\texttt{day}_{i,t}$. Similarly, $(1-\mathbb{D}_{i,t}) \times (\texttt{day}_{i,t})^s$ is the interaction term between $1-\mathbb{D}_{i,t}$ and the sth polynomial term of $\texttt{day}_{i,t}$. As is common in RD, we use box kernel for all our RD regressions. Note first that our dependent variable, $\texttt{esales}_{i,t}$, is normalized by the merchant's average sales before loan disbursal, and second, the running variable day is centered around the date of disbursal. Thereby, the coefficient τ gives us the measure of discontinuity relative to average sales at the day of disbursal (at day = 0). The intercept α gives us an estimate for the counterfactual sales relative to average sales, at day = 0.

The selection of the bandwidth h creates a trade-off between bias and precision. A wider bandwidth allows including more data points, farther away from the cut-off (see, e.g., Imbens and Lemieux, 2008; Lee and Lemieux, 2010) and thus, for fitting a high order polynomial, more data points may help us capture non-linearities in the data more precisely in a flexible way. However, as we include more data away from the cut-off, we run the risk of including the effects of other events taking place away from the cut-off. Moreover, as discussed earlier, exceptional sales days that close the preceding loan may accentuate the discontinuity for the following loan. For this reason, we only include those repeat loans in any analysis that were disbursed *more than h* days after the closure of the borrower's preceding loan. This allows us to keep the effects of exceptional closure day sales, if any, subdued in the bandwidth of analysis. When we apply a wider window with this exclusion criterion, we exclude more repeat loans but have more observations on transactions per loan. For these considerations, we select

a narrow bandwidth of $h = 7$ for all baseline local regressions and figures. Keeping up with the good practice suggested by Lee and Lemieux (2010), we cross-validate our findings using wider bandwidths as well. For most of our results, we report local regressions with a narrow bandwidth ($h = 7$), as well as the widest bandwidth of $h = 90$ at the other extreme. We also report some other intermediate bandwidths for the main results. Readers may ask us for regression results for those specifications not reported in the paper.

Following the suggestions of Hausman and Rapson (2018), we select the number of polynomial terms to the left (p) and to the right (q) of the cut-off based on the Bayesian information criterion (BIC) . The BIC allows capturing a trade-off between precision and the number of estimated parameters. We select the specification with the lowest BIC from a grid search across all combinations of p and q, allowing a maximum order of 7. The BIC selection criteria suggests $p = q = 1$ regardless of the sample, for any local regression with a bandwidth of $h = 7$. Essentially, that means we run a *local linear regression* every time. When cross-validating with wider bandwidths, the BIC selection criterion does not choose a polynomial fit with an order higher than 3 for any sample or bandwidth. For inference, throughout our analysis, we apply standard errors clustered over loans. We run the RD regressions for different samples of borrowers. Doing this across samples helps us answer (i) which borrower types show sales diversionary behavior? (ii) How is sales diversionary behavior linked to default? (iii) How is strategic default linked to outside opportunity? (iv) How is diversionary behavior linked to cash availability? For the definitions of the samples, see Table A1 in Appendix A.

5   Results

5.1   Baseline Visual Evidence and Regression Estimates

To study borrowing merchants' sales behavior around their loan disbursals, we trace their digital sales in the 7-day period before disbursal and in the 7-day period, starting on the disbursal day, after disbursal. With this, we record our first result–the remarkable heterogeneity in how merchants respond to disbursal. First, merchants appear to exercise more control over their sales as they become more experienced. While the repeat loan takers do not show any particular change in sales around disbursal in their first loan, we observe a sharp, discontinuous fall in sales right after the disbursal in their subsequent loans. Actually, this discontinuous fall in sales post-disbursal is led by loans that became non-performing (delayed or in default). Because we argue in the next section that observed discontinuity could be explained only by a voluntary diversionary action, the discontinuity by non-performing loans points to the voluntary nature of default and delay.

Second, much like the first loan of the repeat borrowers, one-time borrowers (non-repeat borrowers) do not show any consistent suspicious behavior around disbursal. Third, non-repeat or repeat borrowers whose loans end as performing also do not exhibit any discontinuity in

sales around disbursal. Thus, the discontinuous drop in sales is uniquely associated with repeat borrowers and their non-performing repeat loans.

Figure 3 and Figure 4 plot, in a narrow window around loan disbursal, the digital sales of the borrowing merchant against *days since disbursal* (day). Negative days since disbursal (day < 0) indicate days before disbursal and day = 0 is the disbursal day. The points on these figures represent the mean digital sales per merchant and the solid lines are the fit estimated from the local linear regression as described in Equation 1 with day as the running variable. The regression results for different samples that feature in these figures are given in Table 6 and Table 7.

Figure 3 compares the borrower sales corresponding to non-performing loans with those corresponding to performing loans for the seasoned borrowers who took more than one loan from the fintech payment company. A few interesting things stand out here: first, as discussed above, merchants with non-performing loans show discontinuity but only on their second and subsequent loans. Remember that non-performing loans are those loans that either went into default or were delayed 30 days beyond their implied due date. Because a defaulting borrower does not receive another loan, all the non-performing *first* loans are basically loans in delay. Thus, our result implies those merchants who were delayed on their first loan do not reduce their sales discontinuously. Reduced sales is a behavior that we observe in the non-performing repeat loans only.

The regressions in Table 6 confirm the visual evidence. Moreover, from the regressions for the non-repeat borrowers in Table 6 and in Figure 4, we see that the non-repeat borrowers do not exhibit any discontinuous reduction. Taken together, this evidence points to some learning effects, where merchants learn through their experience over loans that they could manipulate their sales to evade loan enforcement. Fink, Jack and Masiye (2020) also find similar results in the context of micro consumption loans in rural Zambia, where borrowers showed much lower repayment rates on their repeat loans due to borrowers gaining the insight that the lender had limited power to enforce loans.
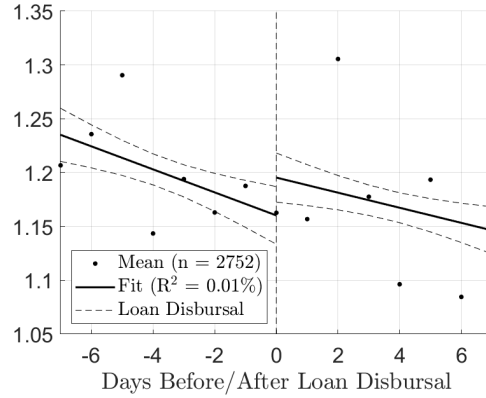
Because the sales are normalized by the merchant's long-term average sales, the value of transactions bigger than one implies that the merchant's sales are above the long-term average. Further, the estimate for discontinuity gives us the change in sales relative to the average. This way, we can easily determine the change in percentage points of average sales. From regression results, we observe that borrowers, on average, drop their sales by about 18 percentage points right after loan disbursal on repeat loans that end as non-performing loans. The drop is economically significant not only for the large drop but also because it pushes down the sales from above the long-term average pre-disbursal to below the long-term average post-disbursal. The sales post-disbursal depress to about 17% below the long-term average. We also run a similar regression as in Table 6 but with *daily number of transactions* as the dependent variable. We find a similar discontinuous drop in the number of transactions for non-performing loans. However, from the regression results in Table A5 in Appendix A, the

Figure 3: Merchants' Normalized Transaction Value Pre- and Post- Loan Disbursal

Performing Loans, Repeat Borrowers
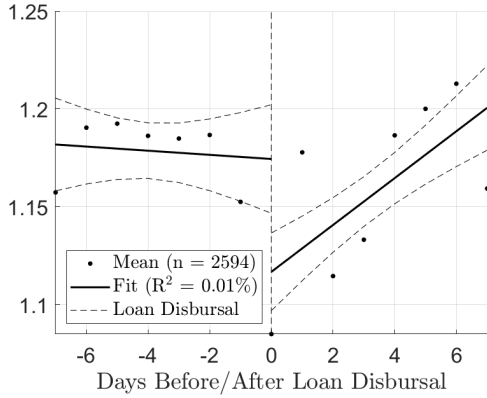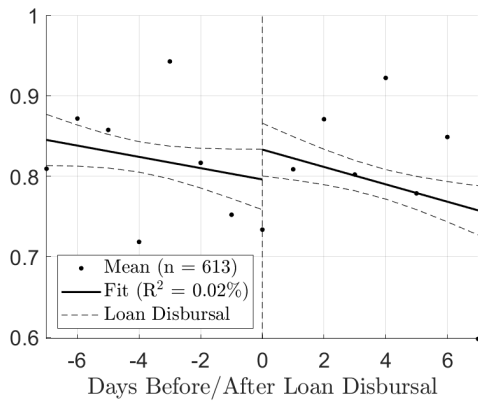

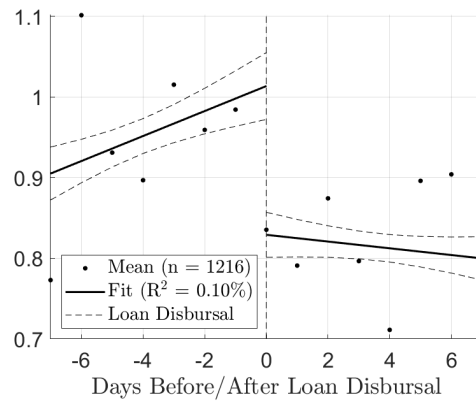(a) 1st Loan   (b) Repeat Loan

Non-performing Loans, Repeat Borrowers
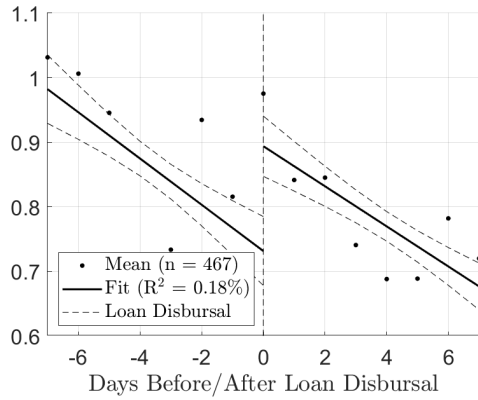

(c) 1st Loan   (d) Repeat Loan

Points on the graphs represent the mean of the normalized daily transaction values over merchants. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). On the horizontal axis, 0 represents the day of disbursal and negative integers refer to days before disbursal and positive integers refer to days after disbursal. Solid lines represent the fit by a local regression for a 7-day window around disbursal. Dashed lines show 95% confidence interval using standard errors clustered by loan. Dashed vertical line shows date of loan disbursal. *n* in the legend refers to number of loans (number of borrowers). Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 7 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. For detailed definitions of samples see Table A1.

drop is about 11 percentage points in the number of transactions, as against the 18 percentage point in the value of transactions, implying that merchants divert high-value transactions first.

Figure 4: Merchants' Normalized Transaction Value Pre- and Post- Loan Disbursal

Late Loans

(a) Non-Repeat Borrowers
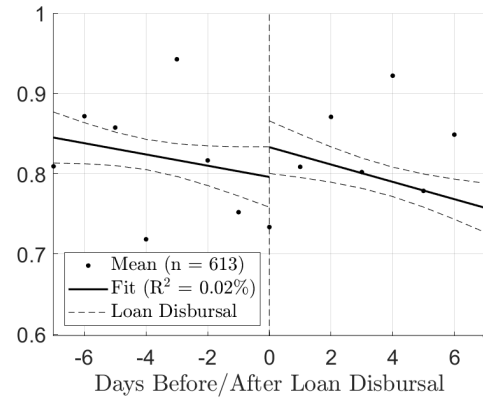
(b) Repeat Borrowers, 1st Loan
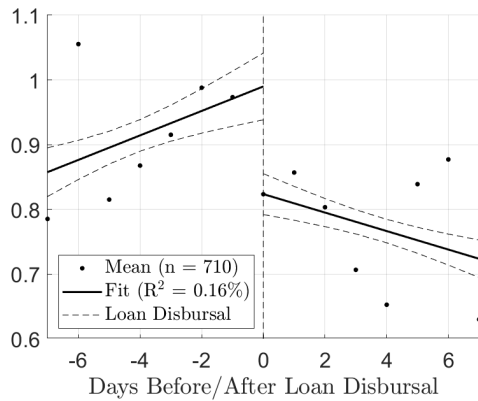
(c) Repeat Borrowers, Repeat Loan

Default Loans

(d) Non-Repeat Borrowers
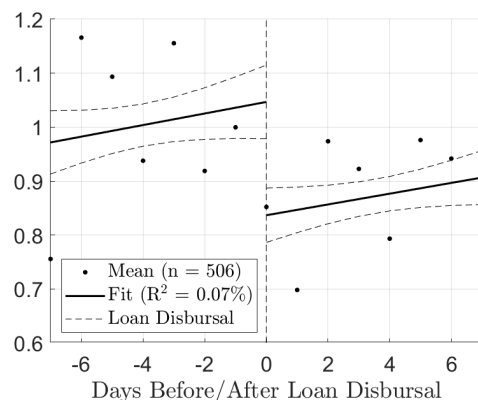
(e) Repeat Borrowers, Repeat Loan

Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. n in the legend refers to number of loans (number of borrowers). For more details see notes for Figure 3 and for detailed definitions of samples see Table A1.

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To understand the non-performing loans more deeply, we run regressions separately for late loans and default loans in Table 7. Within the group of non-performing borrowers, while both delayed and default loans show discontinuity, the estimates of discontinuity are higher for defaulting loans. In the case of repeat loans that eventually run into default, the borrowing merchants' sales show a bigger fall instantly after disbursal. These merchants drop their sales by 21 percentage points, resulting in a value that is about 16% below its long-term average post-disbursal. For these loans, the borrowers' pre-disbursal sales average 5% above their long-term average. For the eventual late loans, the drop is 17 percentage points post-disbursal from approximately the same level as the long-term average pre-disbursal. Another interesting feature associated with borrowers with repeat non-performing loans is that their sales show a slight upward trend before disbursal (Figure 3 and Figure 4). In contrast, all other borrower samples, including borrowers with repeat performing loans, show a downward trend in sales before disbursal. These trends also point out that borrowers who appear to manipulate their sales post-disbursal more are also likely doing it before disbursal, perhaps to give a rosy picture of their business before acquiring the borrowed funds. However, from regressions, we observe that the slope of the sales pre-disbursal is not precisely estimated. Therefore, we exercise caution in making this inference.

We also note that first performing loans of the non-repeat borrowers show a significant positive jump in sales post-disbursal. However, this result is not robust to alternative bandwidths as the estimate of discontinuity becomes insignificant and even negative for larger bandwidths as shown in Tables C8 through C10 in Appendix C. Similarly, a downward jump showed by repeat borrowers with a performing first loan in the first panel of Figure 3 is not statistically significant and changes signs for different specifications of the bandwidth. However, the discontinuous fall recorded in the sales of the experienced borrowing merchants with non-performing loans is robust across all the bandwidth specifications in Tables C8–C10. These results bring to the fore the issues of limited enforcement and voluntary default by highlighting that defaulting borrowers manipulate their sales. We discuss them next.

5.2   Discussion: Discontinuity and Sales Manipulation

Having learned that the discontinuity in transaction value after loan disbursal for particular kinds of borrowers is quite striking, in this section, we explore some alternative explanations of a discontinuous drop in the sales. We argue that no argument other than sales manipulation can convincingly explain the discontinuity. Following that, we relate our observations about discontinuity with the borrower's motives for sales manipulation.

The first alternative explanation is that discontinuity may result if the disbursal coincided with a common exogenous negative shock to merchants' sales. However, in our study, loans are not concentrated in one period and rather spread over 13 months; therefore, it is unlikely for such a coincidental shock to drive the results. Now, given that we observe discontinuity in

Table 6: Performing vs. Non-Performing Loans

Dependent Variable: Total Daily Transaction Value (normalized, 7-day window)

	All	Performing Loans			Non-performing Loans		
	Brwrs.	Non-rep.	Repeat Borrowers		Non-rep.	Repeat Borrowers	
	& Loans	Brwrs.	1st Loan	Rep. Loan	Brwrs.	1st Loan	Rep. Loan
Intercept	**1.05*****	**1.01*****	**1.17*****	**1.16*****	**0.72*****	**0.80*****	**1.01*****
	(0.02)	(0.06)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)
$(1-\mathbb{D}) \times$ day	**-0.01****	**-0.05******	-1.1E-03	-0.01	**-0.04******	-7.0E-03	0.02
	(4.8E-03)	(0.02)	(9.1E-03)	(9.0E-03)	(0.01)	(0.01)	(0.01)
Discontinuity, $\mathbb{D}$	4.5E-03	**0.18******	-0.06	0.04	0.09	0.04	**-0.18******
	(0.03)	(0.07)	(0.05)	(0.05)	(0.07)	(0.08)	(0.07)
$\mathbb{D} \times$ day	-5.1E-03	**-0.03****	**0.01***	-7.0E-03	**-0.02***	-0.01	-4.2E-03
	(3.6E-03)	(0.01)	(7.0E-03)	(7.5E-03)	(9.3E-03)	(0.01)	(9.1E-03)
No. Loans	9,327	1,112	2,594	2,752	1,040	613	1,216
No. Obs.	139,905	16,680	38,910	41,280	15,600	9,195	18,240
R^2	0.02%	0.14%	0.01%	0.01%	0.24%	0.02%	0.10%
$\bar{R}^2$	0.02%	0.11%	-0.00%	0.00%	0.22%	-0.02%	0.08%
Bandwidth (h)	7	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0	0

Results from local regression of merchants' normalized daily transaction value as dependent variable. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). Regression uses the number of days since loan disbursal (day) as running variable. The day number is centred around day of loan disbursal, such that day = 0 for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{D}$ is a dummy variable that takes value 1 if day $\geq$ 0 and 0 otherwise. Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 7 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Local regression is performed using a box kernel, over a 7 day bandwidth. Number of polynomial terms on each side of cut-off correspond to the specification with the lowest BIC.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

the sample of borrowers with repeat non-performing loans, we need to also be sure that such loans were not concentrated at a specific time period. As evident from Table A2 in Appendix A, repeat loans were also spread over several months–admittedly not uniformly. Further, we test whether the results for the sample of repeat non-performing loans hold if we exclude all the loans disbursed in a particular month from the sample. Results of this exercise with exclusion performed for each of the 13 months at a time are presented in Table C11 in Appendix C. The results point that for each excluded month, the estimate of discontinuity stays significant and negative for the remaining sample. Moreover, the estimates of the drop in sales in the remaining sample are quite stable across different exclusions staying close to the 18 percentage point drop observed for the full sample of repeat non-performing loans.

Table 7: Late and Default Non-Performing Loans

Dependent Variable: Total Daily Transaction Value (normalized, 7-day window)

	Late Loans			Default Loans	
	Non-repeat	Repeat Borrowers			
	Brwrs.	1st Loan	Repeat Loan	Non-rep Brwrs.	Repeat Loan
Intercept	0.73***	0.80***	0.99***	0.71***	1.05***
	(0.08)	(0.06)	(0.08)	(0.09)	(0.10)
$(1-\mathbb{D}) \times$ day	-0.04*	-7.0E-03	0.02	-0.05**	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Discontinuity, $\mathbb{D}$	0.16	0.04	-0.17*	0.03	-0.21*
	(0.11)	(0.08)	(0.09)	(0.10)	(0.12)
$\mathbb{D} \times$ day	-0.03**	-0.01	-0.01	-7.7E-03	1.0E-02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
No. Loans	467	613	710	573	506
No. Obs.	7,005	9,195	10,650	895	7,590
R^2	0.18%	0.02%	0.16%	0.34%	0.07%
$\bar{R}^2$	0.12%	-0.02%	0.12%	0.30%	0.02%
Bandwidth (h)	7	7	7	7	7
Cutoff	0	0	0	0	0

Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Implied tenure is the number of days in which the loan should have been fully repaid if the borrowing merchant in the post disbursal period continued his pre-disbursal long term average sales. Default loans are loans with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1. For detailed notes on regressions see Table 6.

Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Taking a cue from our overall result in the previous section, another way to rule out any aggregate shock is to check if the same heterogeneity across samples exists for the loans made on the same dates. The idea is that if among the loans having a common date of disbursal, some show discontinuity but others don't, then the discontinuity cannot be driven by common shocks. This is what we study in Appendix C.3. We compare borrower sales around the disbursal of *non-performing first* loans with the sales around the disbursal of *non-performing repeat* loans that were disbursed on the same dates as the former. Figure C8 shows the latter sample of borrowers shows a discontinuity in sales while the former does not. In the second part of Figure C8, we find among repeat borrowers who received their repeat loans on the same dates, performing loans did not show discontinuity while non-performing loans did, again ruling out any common shock. Table C12 presents the regression results confirming this in disbursal-date matched samples.

The next alternative explanation is about idiosyncratic factors. In particular, merchants could be accepting loans based on their signals about future expected shocks. If borrowers could *anticipate* when an idiosyncratic shock, for example, loss of some of their regular customers, might occur, they could time their loan such that they receive a loan at the same time the

shock hits them. This would be a case of *adverse selection*, where merchants who have private information about a looming negative shock take the loan. If this is so, we will attribute *realization of business-specific shock* to sales manipulation.

However, there are some reasons that cast strong doubts about the anticipation argument. First and foremost, it is highly implausible that merchants would get their predictions perfectly right such that the shock and loan disbursal always coincide. There are two reasons for this implausibility: one is that there will usually be an error between expectation and realization of the shock—the shock may arrive earlier or later than expected. In addition, even though repeat borrowers might have a good understanding of the loan disbursal process, there is still some uncertainty at the time loan application on exactly when the loan amount will arrive in their bank account. Therefore, under the anticipation explanation, where the expected shock may realize earlier or later than the disbursal date, we should not observe any discontinuity at any one particular cut-off close to the disbursal date. However, the discontinuity observed for the non-performing repeat loans precisely at day $= 0$ is indisputable, and it is robustly observed under various specifications of the sample. This behavior can only be the case under anticipation explanation if merchants make no (or few) errors in not only anticipating the shocks but also in synchronizing the arrival of the shock with the loan disbursal. This is highly implausible.

In addition, quite distinctively, borrower sales for repeat non-performing loans show a rising trend before disbursal. It, therefore, becomes less plausible that borrowers can predict a shock in the midst of such a rising trend. The positive slope coefficient suggests that before disbursal merchants increase sales about 2 percentage points of their long-term average sales, per day. Admittedly, although positive, the slope coefficient is not significant (Table 6). However, consistent with the positive trend in transaction volume, there is a significant and positive slope coefficient for the *number of transactions* in the regression in Table A5. Regression in Table A5 suggests that these merchants increase their number of transactions by an average of one percentage point per day in the days leading up to disbursal. Further, for the wide 90-day bandwidth we have tried more flexible polynomial specifications to capture non-linear changes in transaction values pre-disbursal, and we find that sales for these borrowers always shows an increasing trend in the days before disbursal.[25] Therefore, we conclude that the discontinuity in sales on the disbursal day appears to be evidence of a concerted effort to divert sales.[26]

What are the motives behind the sales diversion that reflect as the discontinuous drop in sales post-disbursal? Merchants could divert sales *briefly* post-disbursal to minimize immediate deductions going towards repayment to maximize the liquidity available to them. In such a scenario, merchants may make up for the diverted loan repayments by increasing their sales

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[25]These results are available on request.

[26]Another alternative explanation—which we can rule out—would be that the discontinuity may be the result of weekly seasonal effects showing up in the aggregated time series despite heterogeneous disbursal weekdays. Appendix C.4 discusses this concern in more detail. However, our results remain valid even when controlling for such seasonality (see Table C13).

later or by paying the lender directly, without being delayed. Moreover, if the merchant reduces sales only for a few days, then in the absence of any additional actions described above, loan repayment may get delayed only by a few days. Even then, in our measure of delay, such a loan will be counted as performing because we call a loan late only if it is 30 days or more beyond the implied due date. Therefore, if diversion for short-term liquidity management is the motive, we will observe discontinuity in sales for the borrowers with performing loans as well. Further, the discontinuity should be especially pronounced in *repeat* performing loans if we expect merchants to learn from their borrowing experience how to steer their sales to manage liquidity. However, our results do not support evidence for such a motive. We do not observe any discontinuous fall in sales associated with either first or repeat performing loans. From the local linear regressions in Table 6, we see that performing loans have insignificant and/or positive discontinuity. In the larger bandwidths, sometimes we do observe a negative estimate of discontinuity, but it is not robust across all bandwidths.

Alternatively, merchants may manipulate sales in order to lengthen their *effective tenure*. Essentially by reducing their sales passing through the payment company POS, the borrowing merchant may convert a "short-term" loan to a "long-term" . Finally, merchants may manipulate because they voluntarily default. A merchant may not default (abscond) immediately after disbursal by diverting all digital sales going through the payment company to zero. Rather, the merchants may do so gradually as it may take time to find an effective diversion technology and convince all customers to pay in cash, for instance. Our results are consistent with these explanations because we observe the discontinuity for the sample of late and default borrowers. In summary, the main conclusion of this section is that the existence of discontinuity and the nature of discontinuity points to merchants manipulating their sales to *voluntarily* delay or default. This result casts a shadow over the effectiveness of the payment company enforcement and brings to the fore the issue of strategic default in an environment with weak enforcement. The next two sections dig deeper into understanding some factors that may weaken this enforcement mechanism.

5.3   Lending Market Competition and Enforcement

Competition among lenders weakens enforcement. Having access to credit from other sources diminishes a borrower's incentive to maintain a relationship with the current lender. Therefore, we expect borrowers who have better opportunities outside of their credit relationship with the lender, i.e., those borrowers with better access to the credit market, to show a behavior of strategic default. Similarly, we expect borrowers who have limited access to the credit market outside of their relationship with the lender to not default strategically.

An indicator of ease of market access for a borrower is the borrower's credit score. Borrowers who have no credit history (no credit scores) have limited access to the credit market. Among the borrowers who have credit scores, those with higher credit scores have better access to

credit. However, using credit scores as a proxy for outside opportunities and linking that access with loan outcomes could potentially be impaired by endogeneity issues. First, lenders usually consider a borrower's credit scores when making a loan decision. Therefore, the loan outcomes we observe will not just be the result of a borrower's outside opportunity but also a lender's response to that opportunity. Second, a borrower's opportunistic behavior will be limited by the lender's reporting practice to the credit bureau because that affects a borrower's future credit scores.

In our case, however, we are fortunate that these issues do not arise. As for the issue of lender factoring in the credit scores, our lender did not use the credit scores at any stage in the life of these loans. The lender solely relied on the data relating to the merchants' historical sales for loan decisions. We can confirm this claim of the lender from our data in many ways. First, the fact that about 10% of the borrowers were unscored (had insufficient credit history) at the time of the borrowing indicates that lender heavily relied on past sales data.

Second, most significantly, among the loans for which the borrowers had scores, none of the ex-ante loan contract terms correlate with credit scores. The three most important loan contract terms are the interest rate, the deduction rate, and the loan amount. As discussed above, the interest rate for all the loans was identical at 2% per month. The deduction rate at the time of borrowing was fixed at 10%. So, these two contract terms were by design independent of credit score (or even historical sales). The loan amount for both first loans and repeat loans does not appear to have any correlation with the credit scores, too. This is apparent from the Figure 5. The figure also shows, not surprisingly, that average past sales are highly correlated with the loan amount.

Finally, as another test to confirm the lender's claim, we look for any possible sorting of borrowers that the lender might have undertaken based on some cut-off level of credit scores. Because a sorting at any cut-off will produce a discontinuity in the density of the credit score, we can test for sorting by testing for the presence of a discontinuity in the density of credit scores at different credit score thresholds. This is the idea of McCrary (2008). We perform the McCrary test at different levels of credit scores in Figure A3 in Appendix A and find no evidence of discontinuity anywhere. Notably, there is also no discontinuity around the score 700, which is considered to be a threshold between a good and a bad credit score.

Our analysis is impervious to the issue of credit reporting because our lender, like the other fintech payment companies, did not report to the credit bureau for these loans. The reason for that could be that these loans do not have the traditional structure comprising well-defined maturity and a fixed amortization schedule. Of course, lenders could introduce such features (for instance, a monthly target) in loan contracts that make these sales-linked loans more aligned with traditional loans and make them amenable to traditional reporting. However, as far as the loans in our study are concerned, credit bureau reporting was not a practice. While we are not sure if the merchants understood this, we think that merchants may have figured that out over their borrowing experience with the payment company.

Figure 5: Loan Amount and Borrower Characteristics: Historical Sales vs. Credit Score

(a) Historical Sales and Loan Amount
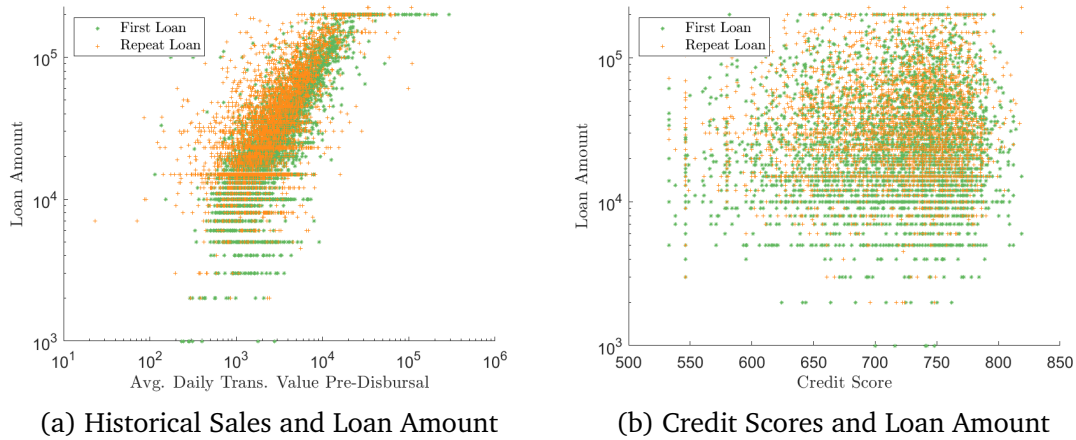
(b) Credit Scores and Loan Amount

Figure (a) shows the scatter between the average per day sales calculated over the 90-day period between 119 days and 30 days before loan disbursal (*Pre disbursal long term average sales*) and loan amount. Figure (b) plots the scatter between credit score and loan amount. Credit scores correspond to that of the merchant owning the business to which the loan was disbursed. TransUnion CIBIL credit scores range between 300 and 900 with higher score indicating better borrower quality as per the bureau's assessment. Figure (b) considers only those loans for which the credit bureau was able to assign a credit score and leaves out merchants who had insufficient credit history (*unscored* merchants). Vertical axes in Figure (a) and Figure (b) showing loan amount are in log scale. Horizontal axis in Figure (a) is in log scale. First loan includes the first (and only) loan of non-repeat borrowers and first loan of the repeat borrowers. Repeat loan refers to second and subsequent loans of the repeat borrowers.

Now, having addressed the two concerns about the endogeneity issues, we analyze how access to credit outside of its relationship with the payment company affects a borrowing merchant's sales behavior post-disbursal. To do that, we divide the sample of borrowers into three categories. The first category comprises borrowers who had a score equal or above 700 at the time of loan disbursal. According to the credit bureau TransUnion CIBIL, borrowers with scores above 700 are considered good by the financial institutions. Therefore, we consider these borrowers as having easier access to the credit market, and hence, a better outside option. The second category of borrowers is those with a credit score lower than 700. These borrowers had a poorer outside option at the time of their loans. The third category of borrowers is the unscored borrowers, who had no credit scores due to insufficient credit history. These borrowers can be thought of as having the poorest outside option.

Figure 6 and Table 8 present the result of local regression for these three categories of the borrowers. Our focus again is repeat, non-performing loans. We see that borrowers with a score above 700 whose loans end up as non-performing show a significant discontinuous drop in sales immediately after disbursal. Borrowers with a credit score less than 700 show negative discontinuity as well, but it is not significant. Further, the result for < 700 is also not robust to wider estimation windows, and the discontinuity estimate turns positive in a 90-day window (Table A6). Finally, for the unscored non-performing loans, borrowers also do not show any

discontinuity in sales. Thus, we find greater evidence of sales manipulation for borrowers with better outside options.

Table 8: Merchants' Sales Around Loan Disbursal by Credit Score

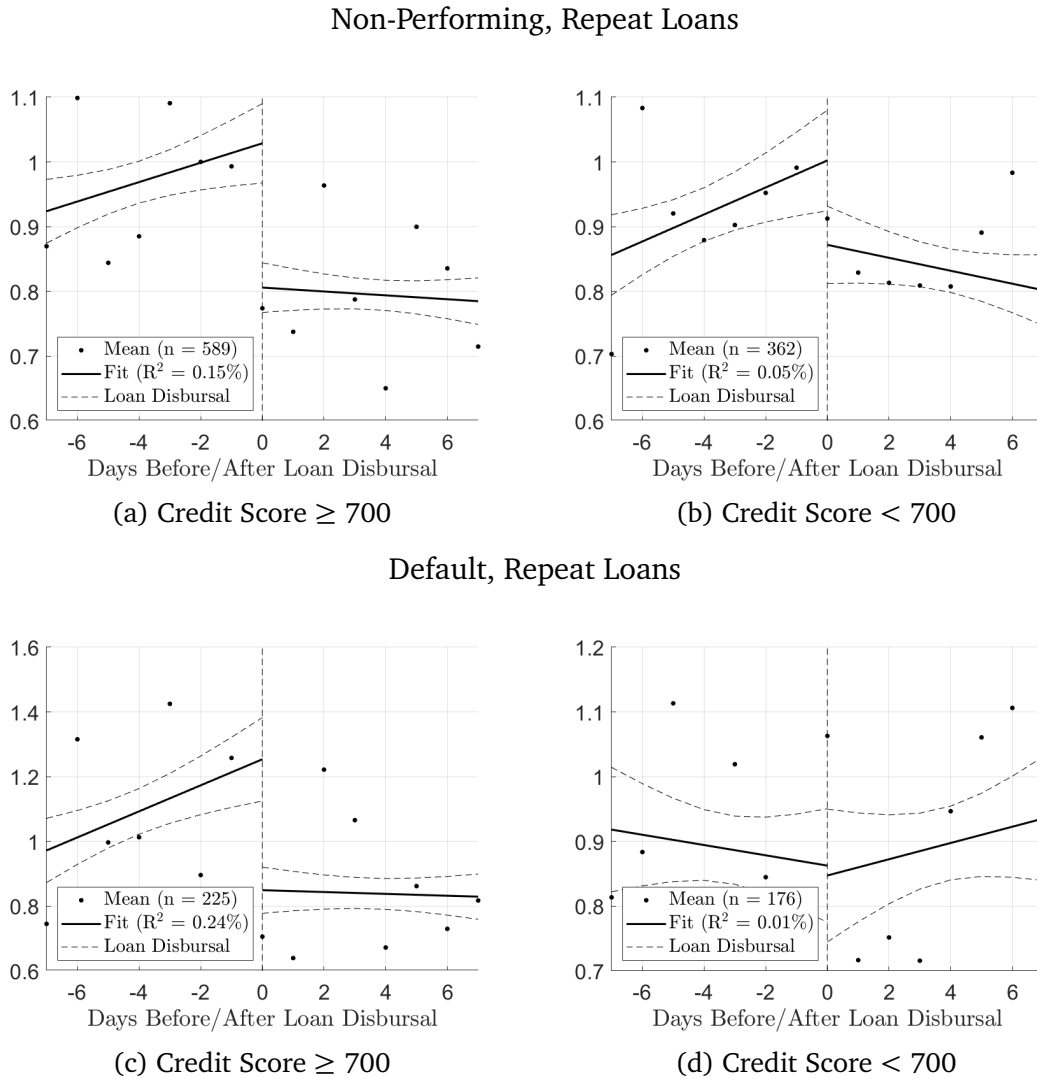Dependent Variable: Daily Transaction Value (normalized, 7-day window)

	Non-performing, Repeat Loan			Default, Repeat Loan		
	≥ 700	< 700	Unscored	≥ 700	< 700	Unscored
Intercept	**1.03*****	**1.00*****	**0.88*****	**1.25*****	**0.86*****	**0.59*****
	(0.09)	(0.12)	(0.32)	(0.19)	(0.13)	(0.20)
$(1 - \mathbb{D}) \times$ day	0.01	0.02	5.9E-04	0.04	-7.9E-03	**-0.08***
	(0.02)	(0.02)	(0.06)	(0.04)	(0.03)	(0.05)
Discontinuity, $\mathbb{D}$	**-0.22****	-0.13	0.05	**-0.40****	-0.02	0.20
	(0.10)	(0.14)	(0.24)	(0.20)	(0.20)	(0.27)
$\mathbb{D} \times$ day	-3.0E-03	-1.0E-02	-0.04	-2.9E-03	0.01	0.02
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.07)
No. Loans	589	362	72	225	176	28
No. Obs.	8,835	5,430	1,080	3,375	2,640	420
R^2	0.15%	0.05%	0.16%	0.24%	0.01%	0.64%
$\bar{R}^2$	0.11%	-0.03%	-0.22%	0.12%	-0.14%	-0.32%
Bandwidth (h)	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0

 Regression samples include only repeat loans (second and subsequent loans), and only those that were disbursed more than 7 days after the closure of the previous loan of the borrower. Standard errors are clustered by loan and presented in parentheses. Credit scores correspond to that of the merchant owning the business to which the loan was disbursed. Credit scores range between 300 and 900. Scores above 700 are assessed as good by the credit market. For the unscored loans, the borrowers did not have a long enough credit history at the time of the borrowing to have been assigned any score by the credit bureau. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall $> 5\%$ of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1. For detailed notes on regressions see Table 6.
 Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

To study the incidence of strategic default and its link with the competitive lending market, we study the diversionary behavior of the borrowers who eventually defaulted on their repeat loans. The local linear regression finds a large discontinuous drop in sales post-disbursal for the borrowers with a good score (≥ 700). These borrowers reduce their sales by 40 percentage points instantly after disbursal, bringing sales to about 15% below their long-term average. Notably, these borrowers have counterfactual sales that are 25% above their long-term sales on the eve of disbursal. This dramatic fall in sales following a high sales period points to the voluntary nature of sales diversion and is evidence of strategic default by borrowers who can access credit easily from the credit market. Borrowers with a score of < 700 and those who were unscored do not show a discontinuous drop in sales when defaulting. Note that our results do not suggest that those with a score above 700 are a worse credit risk in the sense that they default more often than those below 700. The results simply tell us that there is evidence that

Figure 6: Credit Scores and Borrowing Merchants' Sales Pre- and Post- Loan Disbursal

Non-Performing, Repeat Loans

(a) Credit Score $\geq$ 700

(b) Credit Score < 700

Default, Repeat Loans

(c) Credit Score $\geq$ 700

(d) Credit Score < 700

Points on the graphs represent the mean of the normalized daily transaction values over merchants. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*Pre-disbursal long-term average sales*). On the horizontal axis, 0 represents the day of disbursal and negative integers refer to days before disbursal and positive integers to days after disbursal. Credit scores correspond to that of the merchant owning the business to which the loan was disbursed. Credit scores range between 300 and 900. Scores above 700 are assessed as good by the credit market. Solid lines represent the fit by a local regression for a 7-day window around disbursal. Dashed lines show 95% confidence interval using standard errors clustered by loan. *n* in the legend refers to number of loans (number of borrowers). Samples consist of only repeat loans. For the 7-day bandwidth, only those repeat loans are considered that were disbursed more than 7 days after the closure of the previous loan of the borrower. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1.

borrowers with credit scores above 700 default strategically when they default. Indeed, the summary statistics in Table A3 in Appendix A suggest that borrowers with scores < 700 have a higher default rate.

A final point is that even if merchants with easy availability of credit from alternative sources have a willingness to default, they may not have the ability to do so if they cannot divert their sales from their payment company. Indeed, in the case of a payment company as the lender, enforcement could be reinstated even in a competitive lending market because the payment company's *senior position in revenue* reduces the borrower's *ability* to default. Because loan repayment in the payment company lending is tied to electronic transactions processed by the company, strategic default is facilitated by competing technologies that help the borrower in diverting sales away from the lender's POS. Next, we explore the technology that can help a borrower divert sales.

5.4   Payment Market Competition and Enforcement

A potential candidate for competing technology is cash, i.e., merchants convince their customers to pay by cash rather than using cards. Other means of diversion of sales are competing payment companies or mobile payment technologies. The source that weakens enforcement is of high relevance. If strengthening enforcement through technology is a policy objective, then should we approach it through *payment system (currency) policy* or *competition policy*? These two are completely different policy domains, after all.

To determine whether cash is the dominant means of diverting sales, we study an exogenous cash-shortage shock that struck a few regions in India in March-April 2018. The idea is that if borrowing merchants show the kind of discontinuity in sales shown above, even in the middle of a cash crunch, then it could imply that merchants use other electronic means, most likely the POS machines of other payment companies, to divert sales. If, on the other hand, we observe no or muted discontinuity in the sales of the merchants in the middle of a cash crunch, then we infer that merchants, at least partly, use cash to divert sales. We use heterogeneity in two dimensions to identify the effect of the availability of cash on a merchant's ability to manipulate sales. First, the cash crunch arrived quite unexpectedly and lasted for a brief period of time. This gives us the opportunity to compare the crunch period with a *non-crunch period* for borrowers from the *same districts*. Second, the cash crunch affected some districts and did not affect others. This gives us the opportunity to compare borrower sales for loans made in crunch districts during the crunch period with loans made in non-crunch districts during the same period.

Given that the drop in sales appears to happen through high ticket size transactions, it is not trivial that cash would be the obvious choice of diversion, because presumably persuading a customer to make a high-value purchase with cash *instead of card* is more difficult for a merchant. On the other hand, diversion of higher ticket sizes is more attractive but because

these firms are small, it is unlikely they would have POS machines from multiple companies to facilitate easy diversion of large transactions. In this scenario, evidence for a cash-led diversion would imply a *fixed cost of persuasion*, such that merchants would employ persuasion for diversion only if it helps them divert a large sum of money.

The cash crunch started in mid-March 2018, with news about ATMs going dry in the Southern states Telangana and Andhra Pradesh.[27] However, by mid-April 2018, the cash crunch spread to several cities across the country and continued to be in the news until the end of April 2018. Note, in contrast to the country-wide cash shortage of November 2016-January 2017 that followed a decision of the government to demonetize the large currency bills on November 08, 2016, the March-April 2018 cash crunch was felt only in certain parts of the country, and it was shorter lived.

Figure 7: Cash crunch episode of March-April, 2018
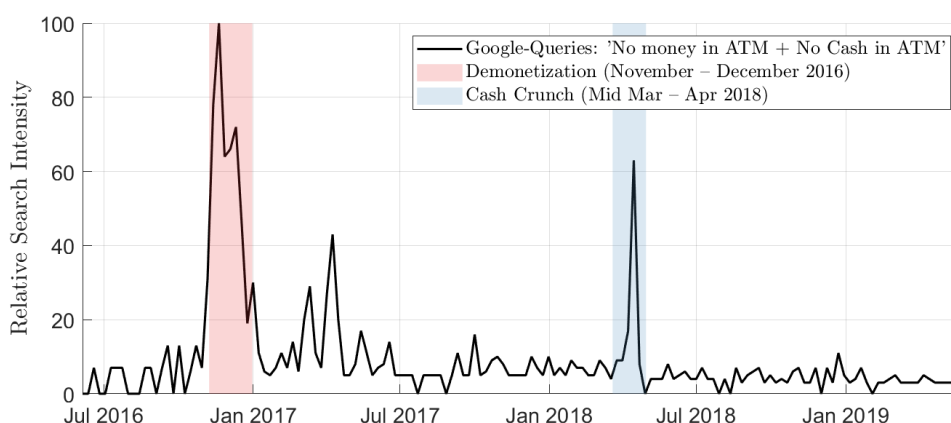
Source: Google Trends. Note: Google searches with terms "No money in ATM" or "No cash in ATM" in the period June 2016-June 2019 in India. Searches are aggregated over weekly window. Figures are in relative terms with maximum number of searches normalized to 100.

Because the 2018 cash crunch did not have any particular day as origin[28] compared to the 2016 demonetization, we rely on news articles[29] and data on Google searches to locate the dates of the cash crunch. Figure 7 provides the rough timeline of the two cash shortages in India. The figure plots the relative number of Google searches for the term "No money in ATM" or "No cash in ATM." The data is normalized such that the highest number of searches are assigned a value of 100. Looking at this figure, we define March 20, 2018, to April 30, 2018,

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[27]See news report in Times of India (March 30, 2018).

[28]The cash crunch resulted due to a combination of several factors. The reasons, among others, included (i) logistical issues, especially delays in calibrating the ATMs to new INR 200 bills, (ii) fear among the public of the newly introduced bail-in clause in the Financial Resolution and Deposit Insurance Bill that proposed that large deposits could be used to bail-in financial institutions and (iii) an unusual currency demand in many states that were going for provincial elections in the upcoming months.

[29]See, for example, Economic Times (April 22, 2018*b*) and Economic Times (April 17, 2018*a*).

as the cash crunch period.

Google trends data is not detailed enough to provide us a good regional decomposition of the search results. Therefore, to determine the cash crunch districts, we look at the digital payment data from our payment company partner for the 'non-borrowers' (merchants who never borrowed from the company in the period up to February 2019). The idea is that in cash crunch districts and in the cash crunch period (20 March-30 April 2018), the number of card transactions should exhibit an *excess* growth when compared to the long-term trend. Appendix B describes our procedure for identifying cash crunch districts in detail. Figure B4 provides examples of how the evolution of the number of transactions differs in crunch and non-crunch districts. Crunch districts have *abnormal* growth in the number of transactions at the end of March and April 2018, while non-crunch districts do not. Table B7 provides the classification of districts into crunch and non-crunch districts.

Our assumption is that the cash crunch was uniformly spread in a district that is found to have had a crunch by our criteria. We look at the transaction values around disbursal dates and make the following comparisons:

1. Loans made in the crunch period in the crunch districts versus loans made in non-crunch districts in the same period.

2. Loans made in the non-crunch period in the crunch districts versus loans made in same districts but in the crunch period.

The non-crunch period consists of the periods 01 October 2017 to 31 December 2017, and 01 June 2018 to 31 July 2018.[30] We focus on the non-performing repeat loans again as those are the loans that show manipulation by the borrowers. However, given that we now work with shorter time periods, we have only a few numbers of loans in each sample. This limitation creates a problem of precise estimation in the local linear regression. Therefore, we employ a longer bandwidth of 90 days as well. Note that as we widen the bandwidth we can include only fewer repeat loans, but we gain on the number of transactions that we observe for each loan.

Table 9 presents the regression results for the four samples of repeat non-performing loans disbursed in (i) crunch period, crunch districts; (ii) crunch period, non-crunch districts; (iii) non-crunch period, crunch districts; and (iv) non-crunch period, non-crunch districts. The same set of regressions is performed for the narrow 7-day bandwidth and a wider 90-day bandwidth. It is reassuring to see that despite the sample differences across the two bandwidths, the discontinuity estimates for any sample are quite similar. The 90-day regressions make the estimates of regression more precise for all samples except for the crunch district in the crunch period. This result suggests that there is much more variation in the sales for borrowers in the

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[30]The idea behind including loans from some pre-crunch months (Oct-Dec, 2017) in the comparison (non-crunch) months was to ensure that the comparison months remain representative. However, keeping in mind that the cash crunch itself might affect the repayment status of the loans (not disbursal day discontinuity, though) disbursed before the crunch, we include loans from the pre-crunch periods that were disbursed sufficiently long before the beginning of the cash crunch to minimize such an effect.

crunch district during the crunch period, indicating that we cannot rule out the absence of discontinuity for this sample even though the estimate for discontinuity is negative. As for the two comparisons mentioned above, first, note that crunch districts in the crunch period show no significant discontinuity while non-crunch districts show a significant discontinuity in the same period. Further, the discontinuity for crunch districts becomes significant and is higher in magnitude in the non-crunch period compared to the crunch period. Finally, the non-crunch districts show a significant discontinuity in both time periods.

Figure 8 plots the merchant transaction values and the corresponding fit from local linear regression across four samples. The figure visually confirms the results of the regressions discussed above. Figure B5 in the Appendix B shows these comparisons for the 90-day window along with a global polynomial fit, with essentially the same conclusions. Taken together, these results imply that borrowers use cash, at least partly, to divert their sales away from the lending payment company, thereby weakening debt enforcement.

Table 9: Sales Manipulation and Cash Crunch

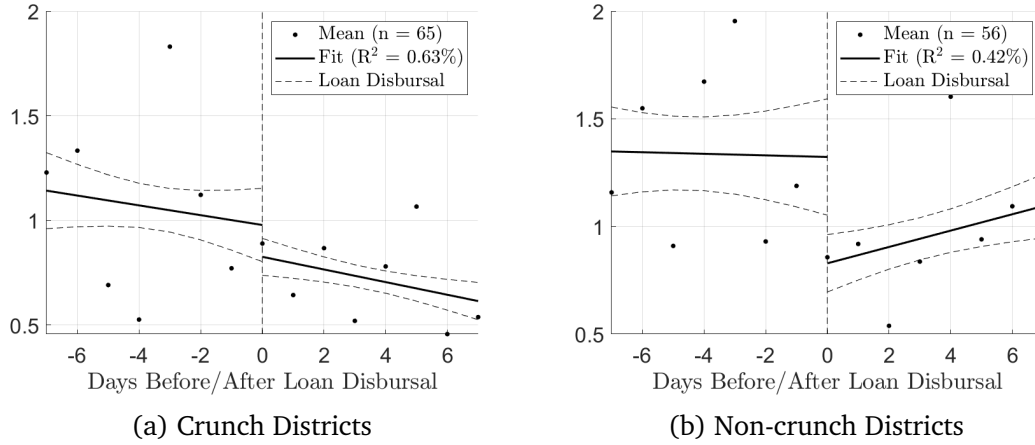Dependent Variable: Daily Transaction Value (normalized, 90- and 7-day window)

| | 90-Day Estimation Window | | | | 7-Day Estimation Window | | | |
| | Crunch Period Mar 20 - Apr 30, 2018 | | Non-crunch Periods Oct 1 - Dec 31, 2017 & Jun 1 - July 31, 2018 | | Crunch Period Mar 20 - Apr 30, 2018 | | Non-crunch Periods Oct 1 - Dec 31, 2017 & Jun 1 - July 31, 2018 | |
	Crunch District	Non-crunch Dist.	Crunch District	Non-crunch Dist.	Crunch District	Non-crunch Dist.	Crunch District	Non-crunch Dist.
Intercept	0.85***	1.51***	0.77***	0.92***	0.98***	1.32***	0.98***	1.10***
	(0.19)	(0.34)	(0.14)	(0.12)	(0.26)	(0.40)	(0.18)	(0.25)
$(1 - \mathbb{I}) \times$ day	-5.4E-04	9.1E-03*	-3.4E-03	-7.7E-04	-0.02	-3.7E-03	0.03	0.01
	(3.3E-03)	(5.1E-03)	(2.6E-03)	(2.0E-03)	(0.06)	(0.07)	(0.04)	(0.05)
Discontinuity, $\mathbb{I}$	-0.16	-0.51***	-0.29*	-0.24**	-0.15	-0.49	-0.29	-0.24
	(0.15)	(0.19)	(0.15)	(0.10)	(0.31)	(0.42)	(0.25)	(0.33)
$\mathbb{I} \times$ day	-3.8E-03**	-8.4E-04	-1.5E-04	-3.2E-03**	-0.03	0.04	-2.8E-03	-2.9E-03
	(1.5E-03)	(2.0E-03)	(1.3E-03)	(1.3E-03)	(0.03)	(0.04)	(0.03)	(0.04)
No. Loans	20	20	18	23	65	56	72	105
No. Obs.	3620	3620	3258	4163	975	840	1080	1575
R^2	0.92%	0.59%	1.74%	1.58%	0.63%	0.42%	0.31%	0.18%
$\bar{R}^2$	0.81%	0.48%	1.62%	1.48%	0.22%	-0.05%	-0.06%	-0.07%
Bandwidth (h)	90	90	90	90	7	7	7	7
Cutoff	0	0	0	0	0	0	0	0

Regression samples consist of only non-performing repeat loans. For the 7-day bandwidth (90-day bandwidth), only those repeat loans are considered that were disbursed more than 7 days (90 days) after the closure of the previous loan of the borrower. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. For detailed notes on regressions see Table 6. Standard errors are clustered by loan and presented in parentheses. Table B7 in Appendix B gives the classification of districts as crunch and non-crunch districts.
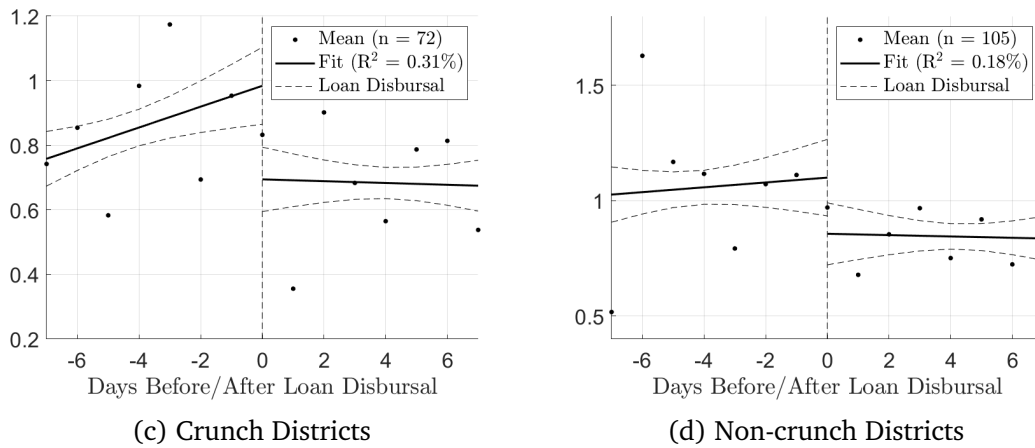Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 8: Cash Crunch and Borrowing Merchants' Sales Pre- and Post- Loan Disbursal

Transaction Value (normalized)

Crunch Period, Mar 20 – Apr 30, 2018

(a) Crunch Districts

(b) Non-crunch Districts

Non-crunch Periods, Oct 1 – Dec 31, 2017 & Jun 1 – Jul 31, 2018

(c) Crunch Districts

(d) Non-crunch Districts

Points on the graphs represent mean of the normalized daily transaction values, over merchants. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*Pre disbursal long term average sales*). On the horizontal axis, 0 represents the day of disbursal and negative integers refer to days before disbursal and positive integers to days after disbursal. Solid lines represent the fit by a local regression for a 7-day window around disbursal. Dashed lines show 95% confidence interval using standard errors clustered by loan. Samples consist of only non-performing repeat loans. *n* in the legend refers to number of loans (number of borrowers). For the 7-day bandwidth, only those repeat loans are considered that were disbursed more than 7 days after the closure of the previous loan of the borrower. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. Table B7 in Appendix B gives the classification of districts as crunch and non-crunch districts.

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6 Conclusion

Fintech payment companies across the globe are moving into lending. Their lending business is built on two main advantages. The first advantage stems from their ability to generate data and use the economically relevant information about the merchants from the payments they process. The second advantage allows them to enforce debt repayment by achieving *seniority* in the process of intermediating electronic sales for the borrowing merchants. Therefore, fintech payment companies may play a significant role in easing credit market frictions caused by information asymmetry and weak enforcement. This could enhance MSME credit access. We find that the payment company could make uncollateralized loans to MSME borrowers who had no credit history or who had low credit scores. These borrowers would find it extremely hard to access bank credit, especially without collateral..

In this paper, we study the second advantage where the sales-linked debt repayment yields a senior position in the loan for the payment company acting as lender.[31] This mechanism of debt enforcement could be particularly important when enforcement through formal institutions such as courts is costly. Our results point out that the seniority achieved by a payment company lender cannot completely substitute for these enforcement institutions because borrowers could still divert sales away from electronic means. We observe sales diversion as a discontinuous reduction in sales instantly after disbursal. We also discuss that the nature of discontinuity suggests that it is a voluntary act of sales diversion post-disbursal and not the effect of any adverse shock to sales. Because merchants can manipulate their sales, they can still strategically default or delay their repayment.

We find that borrowers who enjoy better access to the credit market outside of their relationship with the fintech lender discontinuously drop their sales immediately after loan disbursal, especially when their loans end up into default. While this result suggests that it is the competitive nature of the credit market that weakens enforcement (Hoff and Stiglitz, 1998), we think the details are more nuanced. Indeed, the easy availability of credit may increase a borrowers *willingness* to default. From the payment company's perspective, the borrower's *ability* to default is determined by the existence of alternative payment technology. This is because only an alternative payment technology can dilute the *seniority* gained by the payment company lender. Using a cash crunch episode that affected various districts heterogeneously, we find that merchants in the cash crunch districts show no significant discontinuity during the crunch period, indicating that they use cash as a diversionary payment technology.

Therefore, in our view, it is the competition in the payment technologies that yield borrowers the ability to default strategically. As the economies move more towards digital payments, this problem could be mitigated to a certain extent as it becomes difficult to substitute cash for electronic payments. Of course, there will always be certain competition, even between

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[31]In a separate paper we study the data advantage of the payment lender and ask whether and how the historical payment data perform better compared to the traditional credit risk metric like credit scores.

different kinds of electronic payment technologies and various payment processors. In that sense, comparatively bigtechs may enjoy more enforcement power because they may provide not only payment services but also online sales platforms. In that case, more than the seniority in payment flow, it is the bigtech's threat of excluding opportunistic borrowers from the sales platform that becomes an effective enforcement instrument. However, sales-linked repayment could be beneficial for other reasons as well. Most notably, these loans provide flexibility in repayment to MSMEs. This flexibility could be valuable to MSMEs that face volatile sales. With flexible repayments, they can share some risk with the lender by paying less in periods with lower sales. Further, the lenders ability to deduct repayment at the source could still be beneficial for the lender in that it might reduce loss given default even in genuine default cases.

Outside of bigtech lending, given that electronic sales are still prone to manipulation and that court enforcement is prohibitively costly, the possibility of strategic defaults may continue to hamper the credit markets, albeit to a smaller degree. Designing flexible sales-linked contracts, when technology makes sales (semi) verifiable and deductible at the source, is a topic of further theoretical research. What we have shown is that in any such design of the contract, the nature of competing payment technologies and institutional environments will play a crucial role.

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Appendix A   Additional Figures and Tables

Figure A1: Ratio of Card Use at POS Terminals to Card Use at ATM
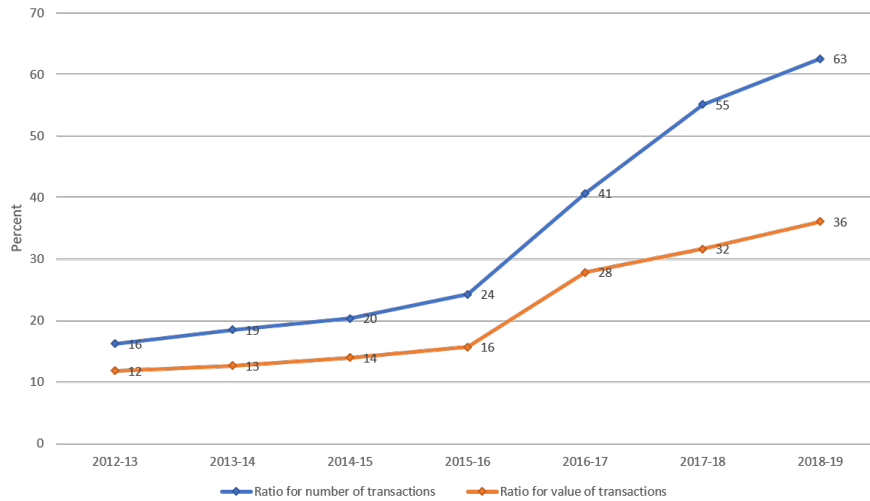
Source: Calculations based on RBI Database on Indian Economy. Note: Cards includes credit and debit cards. Year in this figure refers to financial year in India that runs from April 01 to March 31.

Figure A2: Number of Days Required to Enforce a Contract of Unpaid Debt
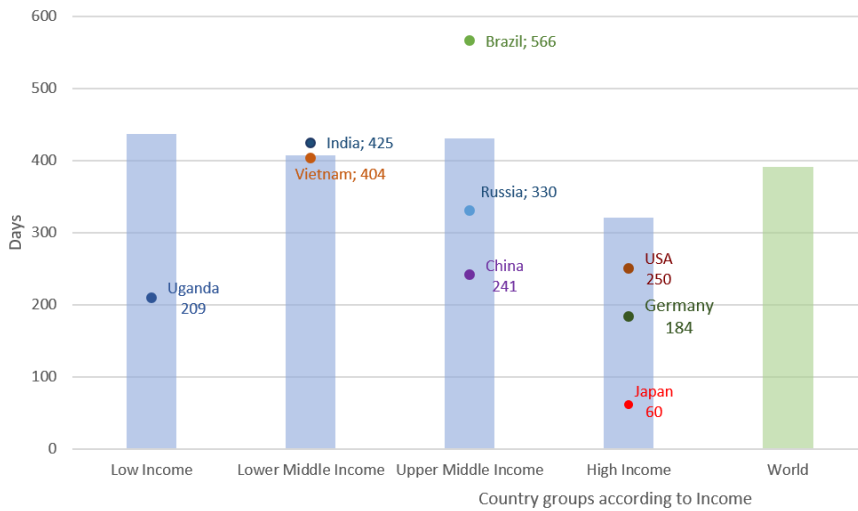
Source: Calculations based on data provided in Djankov, McLiesh and Shleifer (2007). Note: Data is as of January 2003.

Table A1: Definition of Samples

Sample[a]	Definition
Repeat Borrowers	Merchants borrowing multiple times from the lender.
Non-repeat Borrowers	Merchants borrowing only once from the lender (until Feb 2019).
1st Loan	First loan of repeat borrowers.
Repeat Loan	Second or subsequent loan of repeat borrowers. Samples include only those repeat loans where merchant's preceding loan was closed outside of the bandwidth under consideration. For example, if we employ a bandwidth of 7 days in an analysis, we include only those repeat loans that were disbursed at least eight days after the closure of a preceding loan.
Default Loan	Loan with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019.
Late Loan	Non-defaulting loan that took more than 30 days than the implied tenure to fully repay the loan. Implied tenure is the number of days it would take to repay the loan amount, if the merchant continued to transact the average daily transaction value calculated over 90 days between day 119 and day 30 before loan disbursal.
Non-performing Loan	Loan that is either late or in default.
Performing Loan	Loan that is neither late nor in default.

[a] All samples comprise of loans disbursed between October 2017 and November 2018, and loans with 90 or 180 days suggested maturity.

Figure A3: Distribution of Borrowing Merchants' Credit Scores

(a) Density of Credit Scores

(b) Measures of Discontinuity in Density
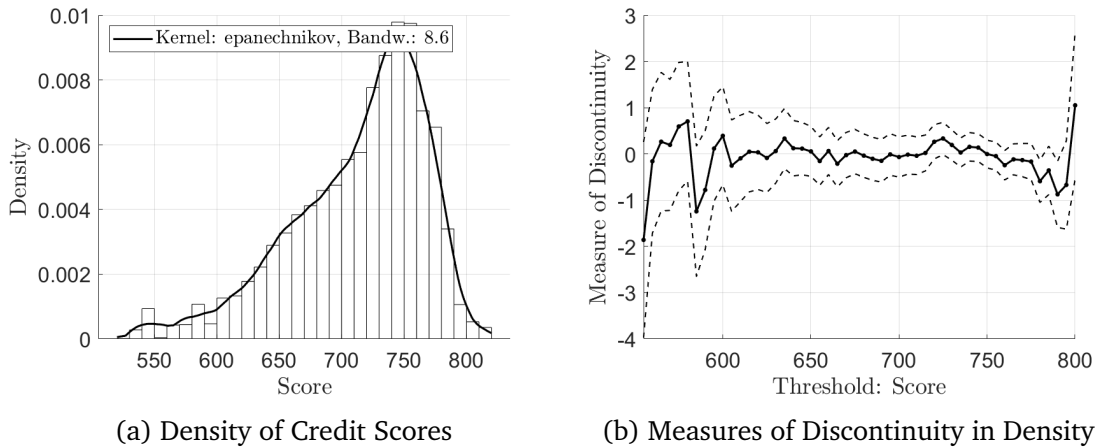
Figure (a) shows the density of borrowing merchants' credit scores (among scored merchants). Figure (b) shows point-wise estimates for the discontinuity in the distribution of borrowing merchants' credit scores for varying credit score cut offs between 555 and 800 as solid black line. Routine to locate discontinuity in density is performed using the *mccrary function* developed in Schäublin (2020) that implements the procedure by McCrary (2008). We use a bin size of 5 and bandwidth of 50 for the routine. Dashed line shows corresponding 95 percent confidence interval. Figure indicates no significant discontinuity in the distribution of borrowing merchants credit scores at any selected credit score.

Table A2: Summary Statistics According to Month of Disbursal

Mean values (except number of loans)

Year-month	No. of Loans	Rep. Loans (%)	Loan Amount (Th. INR)	Sugg. Tenure (days)	Impl. Tenure (days)	Cr. Hist Exists (1 = Yes)	Credit Score	Late (1 = Yes)	Default (1 = Yes)	Non-perf (1 = Yes)
2017-10	108	39.81	52.3	90.0	257.9	0.92	713.8	0.14	0.26	0.40
2017-11	1	0.00	10.0	90.0	70.5	1.00	738.0	0.00	0.00	0.00
2017-12	269	31.97	38.2	90.0	183.8	0.91	718.4	0.20	0.12	0.32
2018-01	409	34.47	44.9	90.0	176.9	0.92	707.6	0.21	0.14	0.34
2018-02	714	42.44	25.2	90.0	139.1	0.90	710.0	0.28	0.14	0.42
2018-03	402	47.51	36.8	90.0	161.1	0.93	714.8	0.31	0.17	0.48
2018-04	947	41.29	36.4	90.0	117.4	0.90	714.2	0.31	0.10	0.41
2018-05	1216	36.68	32.6	90.0	124.0	0.89	719.3	0.28	0.09	0.37
2018-06	889	26.32	33.5	90.0	126.5	0.89	713.4	0.16	0.10	0.26
2018-07	991	26.74	35.6	90.0	118.9	0.90	713.4	0.17	0.10	0.27
2018-08	829	19.54	34.0	101.0	120.6	0.90	713.4	0.12	0.07	0.20
2018-09	747	21.42	42.3	124.8	139.3	0.88	713.6	0.09	0.12	0.21
2018-10	1010	23.66	44.8	152.7	156.5	0.89	714.0	0.12	0.11	0.24
2018-11	795	26.16	55.2	164.4	196.2	0.90	712.2	0.10	0.16	0.26

[a] Among non-defaulting loans.

Repeat loan refers to second and subsequent loans of the repeat borrowers. For details on the variables see Table A1 in the appendix.

Table A3: Summary Statistics by Credit Score Categories

Mean values (except number of loans)

	All Borrowers			Non-repeat Borrowers			Repeat Borrowers					
							1st Loan			Repeat Loan		
	≥700	<700	Unscored	≥700	<700	Unscored	≥700	<700	Unscored	≥700	<700	Unscored
Number of loans	4593	2293	773	1069	466	176	1527	802	297	1997	1025	300
Loan amount (Thousand INR)	39.35	35.88	33.21	38.73	38.32	36.35	31.93	27.46	26.19	45.34	41.36	38.33
Relationship length (months)	14.99	14.84	13.15	13.01	12.35	11.73	12.70	12.33	11.43	17.81	17.93	15.70
Suggested tenure (days)	107.18	106.84	107.70	91.18	90.77	90.51	90.12	90.11	90.00	128.80	127.23	135.30
Implied tenure (days)	142.26	142.24	146.81	114.74	116.47	149.99	101.94	104.32	100.00	187.83	183.63	191.29
Credit score	745.27	651.00		747.08	650.84		744.64	650.06		744.79	651.79	
Days past due (days)	10.02	10.28	6.65	28.80	38.11	29.02	6.81	5.66	5.41	4.00	5.35	-3.19
Implied days past due (days)	-20.70	-13.48	-22.79	10.07	15.26	2.84	-5.01	-8.54	-4.59	-48.63	-27.73	-55.48
Late (1 = Yes)	0.20	0.19	0.17	0.23	0.18	0.22	0.20	0.20	0.17	0.18	0.18	0.15
Default (1 = Yes)	0.10	0.16	0.09	0.22	0.39	0.23	0.00	0.00	0.00	0.11	0.17	0.09
Non-performing (1 = Yes)	0.30	0.34	0.26	0.46	0.57	0.44	0.20	0.20	0.17	0.29	0.35	0.24
Average daily trans (Th. INR)	4.15	3.68	3.37	5.19	4.31	3.86	3.77	3.45	3.18	3.88	3.59	3.26

Credit score is of the business owner at the time of disbursal. The CIBIL credit score ranges between 300 and 900 with higher scores indicating better quality of the borrower. *Unscored* loans are those identified by the credit bureau as having insufficiently long credit history to be assigned any score. Among the scored borrowers, CIBIL indicates that a credit score above 700 is treated as a good score by the credit market. Loans were made between October 2017 and November 2018. All the repeat loans included in the sample were disbursed at least eight days after the closure of the preceding loan of the same borrower. For more details on the variables see Table A1 in the appendix.

Table A4: Summary Statistics on Transactions According to Loan Repayment Status

Normalized Mean values (except number of loans)

	Performing Loans				Non-performing Loans			
	All	Non-rep.	Repeat Borrowers		All	Non-rep.	Repeat Borrowers	
	Brwrs.	Brwrs.	1st loan	Rep. Loan	Brwrs.	Brwrs.	1st loan	Rep. Loan
Transaction value								
180-day window	1.15	1.08	1.18	1.16	0.78	0.75	0.80	0.81
−7 to −1 days	1.19	1.20	1.18	1.20	0.90	0.89	0.81	0.95
0 to 6 days	1.16	1.13	1.16	1.17	0.80	0.75	0.82	0.83
Pre-disbursal long-term	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pre-disbursal short-term	1.10	1.09	1.10	1.10	0.99	1.01	0.96	1.00
Post-disbursal	1.21	1.08	1.25	1.22	0.57	0.48	0.64	0.62
Number of transactions								
180-day window	1.10	1.05	1.12	1.10	0.83	0.77	0.88	0.85
−7 to −1 days	1.11	1.07	1.11	1.12	0.90	0.87	0.87	0.94
0 to 6 days	1.11	1.09	1.11	1.12	0.85	0.79	0.88	0.88
Pre-disbursal long-term	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pre-disbursal short-term	1.06	1.05	1.07	1.05	0.99	0.99	0.98	0.99
Post-disbursal	1.14	1.05	1.18	1.15	0.67	0.55	0.77	0.71
Number of loans	6,458	1,112	2,594	2,752	2,869	1,040	613	1,216

All values, except for number of loans, are average per day per borrowing merchant calculated over a window. 180-day window is centred at the disbursal date and covers 90 days prior and 90 days after disbursal including the day of disbursal. Day 0 refers to the disbursal date. Days with a minus sign are days prior to disbursal. *Pre-disbursal long-term* period refers to the 90-day period between days -119 and -30. It aims to capture the average sales away from the disbursal date. *Pre-disbursal short-term* period refers to the 90-day period between days -90 and -1 and is considered short term for including days shortly before the disbursal. Post-disbursal refers to the 90-day window between day 0 and day 89. We normalize the transaction value and number of transactions by their averages calculated in the *Pre-disbursal long-term* period respectively.

Table A5: Merchants' Transactions Around Disbursal: Performing vs. Non-Performing Loans

Dependent Variable: Daily Number of Transactions (normalized, 7-day window)

	All	Performing Loans			Non-performing Loans		
	Brwrs.	Non-rep.	Repeat Borrowers		Non-rep.	Repeat Borrowers	
	& Loans	Brwrs.	1st Loan	Rep. Loan	Brwrs.	1st Loan	Rep. Loan
Intercept	**1.04*****	**1.05*****	**1.12*****	**1.12*****	**0.79*****	**0.87*****	**1.00*****
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
$(1-\mathbb{D}) \times$ day	-1.6E-04	-9.7E-04	2.4E-03	3.6E-04	**-0.02*****	-1.3E-03	**0.01***
	(2.6E-03)	(7.4E-03)	(4.9E-03)	(5.1E-03)	(7.2E-03)	(8.2E-03)	(7.4E-03)
Discontinuity, $\mathbb{D}$	**-0.05*****	-0.04	**-0.09*****	0.02	0.04	0.03	**-0.11*****
	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)
$\mathbb{D} \times$ day	**0.04*****	**0.07*****	**0.06*****	**-7.3E-03***	**-0.01****	-9.6E-03	-5.9E-03
	(7.4E-03)	(0.02)	(0.01)	(4.4E-03)	(5.4E-03)	(6.6E-03)	(5.5E-03)
$\mathbb{D} \times (\text{day})^2$	**-6.5E-03*****	**-0.01*****	**-7.9E-03*****				
	(9.9E-04)	(2.8E-03)	(1.8E-03)				
No. Loans	9,327	1,112	2,594	2,752	1,040	613	1,216
No. Obs.	139,905	16,680	38,910	41,280	15,600	9,195	18,240
R^2	0.03%	0.09%	0.05%	0.01%	0.24%	0.02%	0.10%
$\bar{R}^2$	0.03%	0.06%	0.04%	-0.00%	0.22%	-0.02%	0.08%
Bandwidth (h)	7	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0	0

Results from local regression of merchants' normalized daily number of transactions as dependent variable. Daily number of transactions is normalized by the merchant's average number of transactions per-day calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average*). Regression uses number of days since loan disbursal (day) as running variable. Day number centred around day of loan disbursal, such that day $= 0$ for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{D}$ is a dummy variable that takes value 1 if day ≥ 0 and 0 otherwise. Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 7 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Local regression is performed using a box kernel, over a 7-day bandwidth. Number of polynomial terms on each side of cut-off correspond to the specification with the lowest BIC.

Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table A6: Merchants' Sales Around Loan Disbursal by Credit Score

Dependent Variable: Daily Transaction Value (normalized, 90-day window)

	Non-performing, Repeat Loan			Default, Repeat Loan		
	≥ 700	< 700	Unscored	≥ 700	< 700	Unscored
Intercept	**0.99*****	**0.64*****	**0.94*****	**1.24*****	**0.66*****	**1.09*****
	(0.08)	(0.09)	(0.11)	(0.20)	(0.13)	(0.18)
$(1 - \mathbb{D}) \times$ day	1.1E-03	**-4.7E-03*****	2.8E-04	5.4E-03	-3.2E-03	2.0E-03
	(1.4E-03)	(1.5E-03)	(1.8E-03)	(3.3E-03)	(2.0E-03)	(3.0E-03)
Discontinuity, $\mathbb{D}$	**-0.26*****	0.03	**-0.28*****	**-0.43****	0.05	-0.32
	(0.07)	(0.09)	(0.10)	(0.17)	(0.12)	(0.21)
$\mathbb{D} \times$ day	**-2.4E-03*****	**-3.8E-03*****	-1.1E-03	**-3.8E-03*****	**-5.2E-03*****	**-2.7E-03****
	(7.0E-04)	(1.1E-03)	(1.2E-03)	(1.5E-03)	(1.5E-03)	(1.3E-03)
No. Loans	127	75	22	42	42	8
No. Obs.	22,917	13,494	3,982	7,602	7,563	1,448
R^2	0.72%	1.26%	1.12%	0.90%	1.44%	1.41%
$\bar{R}^2$	0.70%	1.23%	1.02%	0.84%	1.39%	1.14%
Bandwidth (h)	90	90	90	90	90	90
Cutoff	0	0	0	0	0	0

Regression samples include only repeat loans (second and subsequent loans), and only those that were disbursed more than 90 days after the closure of the previous loan of the borrower. Standard errors are clustered by loan and presented in parentheses. Credit scores correspond to that of the merchant owning the business to which the loan was disbursed. Credit scores range between 300 and 900. Scores above 700 are assessed as good by the credit market. For the unscored loans, the borrowers did not have a long enough credit history at the time of the borrowing to have been assigned any score by the credit bureau. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall $> 5\%$ of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1. For detailed notes on regressions see Table 6.

Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix B   Cash Crunch

Identifying Cash Crunch Districts

We aggregate the *number of transactions* for all *non-borrowing merchants*[32] at the district level and a daily frequency for the period 1 June 2017 to 28 February 2019. Then, for each day in this period, we compute the deviation of the medium-term trend of a district's total number of transactions from the long-term trend. The idea is to capture any unusual or "excess" deviation in transactions in a district compared to its own long-term trend. Districts showing sufficiently high positive deviation from the trend in the period of March–April 2018 can be thought of as ones that faced a cash crunch.

   More precisely, we do the following for each district:

1. Compute a long-term trend value in the number of transactions for each day in the period June 2017–February 2019 by estimating mean, using Epanechnikov Kernel weights, over a six-month window centered around that day (3 months of data on either side of the date).

2. Compute a medium-term trend value of the total number of transactions for each day in the period June 2017–February 2019 by estimating the mean, using Epanechnikov Kernel weights, over a two-month window centered around that day (one month of data on either side of the date).

3. Compute the deviation of the medium-term trend value from the long-term trend value for each day in the sample. To make the differences comparable across districts, we normalize these daily differences by the mean and standard deviation of the differences to obtain a z-score for each district. The mean and standard deviations of the differences are estimated over the sample period but leaving out the crunch period of March 20–April 30, 2018, so as not to let the unusual period affect the calculations of these parameters.

   For steps (1) and (2) we employ the X-13 Matlab toolbox for seasonal filtering by Lengwiler (2021). Among the districts for which we have sufficient loan data, we select those districts as crunch districts where the *maximum z-score* in the crunch period of 20 March—30 April 2018 is bigger than 1.645, and those as non-crunch districts where the maximum of the standardized deviations is below 1.645. For this classification, we consider only those districts that have more than 50 non-borrowing merchants active every month in the period 1 June 2017–28 February 2019. The list of districts classified as crunch and non-crunch are given in Table B7. Figure B4 also provides representative examples of crunch and non-crunch districts, plotting trends in the number of transactions and the z-scores.

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[32]Those merchants who did not borrow in the period until February 2019.

Table B7: Crunch Districts, Number of Merchants and Loans

State	District	Crunch District	Full Period[a]		Crunch Period[b]		Non-Crunch Period[c]	
			All Loans	Brwrs.	Rep. Loans	Brwrs.	Rep. Loans	Brwrs.
Andhra Pradesh	Visakhapatnam	No	57	37	-	-	2	2
Delhi	South West Delhi	No	156	103	4	4	3	3
	West Delhi	No	132	94	2	2	1	1
Gujarat	Ahmedabad	No	101	67	5	5	8	7
Haryana	Faridabad	No	76	50	-	-	3	3
Karnataka	Bangalore	No	2,073	1,330	14	14	36	35
Kerala	Ernakulam	No	59	37	-	-	1	1
Maharashtra	Kolhapur	No	40	22	-	-	2	2
	Nagpur	No	76	50	1	1	2	2
	Pune	No	1,373	895	21	21	35	35
	Raigarh(Mh)	No	119	71	1	1	4	4
	Solapur	No	31	15	-	-	2	2
Punjab	Patiala	No	23	14	-	-	-	-
Rajasthan	Jaipur	No	77	43	2	2	2	2
Tamil Nadu	Chennai	No	368	224	1	1	10	10
	Coimbatore	No	158	99	2	2	7	7
	Kanchipuram	No	372	225	5	5	10	10
	Tiruvallur	No	207	132	1	1	7	7
West Bengal	Kolkata	No	40	26	1	1	1	1
	North 24 Parg.	No	16	13	-	-	-	-
Total Non-Crunch Districts		20	5,554	3,547	60	60	136	134

State	District	Crunch District	Full Period[a]		Crunch Period[b]		Non-Crunch Period[c]	
			All Loans	Brwrs.	Rep. Loans	Brwrs.	Rep. Loans	Brwrs.
Delhi	East Delhi	Yes	111	73	2	2	4	4
	North Delhi	Yes	56	38	2	2	1	1
	North W. Delhi	Yes	42	30	2	2	1	1
	South Delhi	Yes	79	55	-	-	2	2
Haryana	Gurgaon	Yes	126	83	4	4	4	4
Madhya Pradesh	Indore	Yes	127	83	1	1	4	4
Maharashtra	Aurangabad	Yes	53	39	2	2	2	2
	Mumbai	Yes	708	456	10	10	9	9
	Nashik	Yes	97	71	3	3	5	5
	Thane	Yes	967	595	16	16	27	27
Telangana	Hyderabad	Yes	715	453	15	15	27	27
	K.V. Rang.	Yes	238	156	4	4	5	5
Uttar Pradesh	G. B. Nagar	Yes	116	71	6	6	4	4
	Ghaziabad	Yes	148	100	2	2	1	1
Total Crunch Districts		12	3,583	2,303	69	69	96	96

[a] All loans disbursed in the district between October 2017 and November 2018 with 90 or 180 days suggested maturity.
[b] Repeat loans disbursed in district between March 20 and April 30, 2018, with 90 or 180 days suggested maturity.
[c] Repeat loans disbursed in district between October 1 and December 31, 2017, or between June 1 and July 31, 2018, with 90 or 180 days suggested maturity and more than 7 days after the closure of the preceding loan.
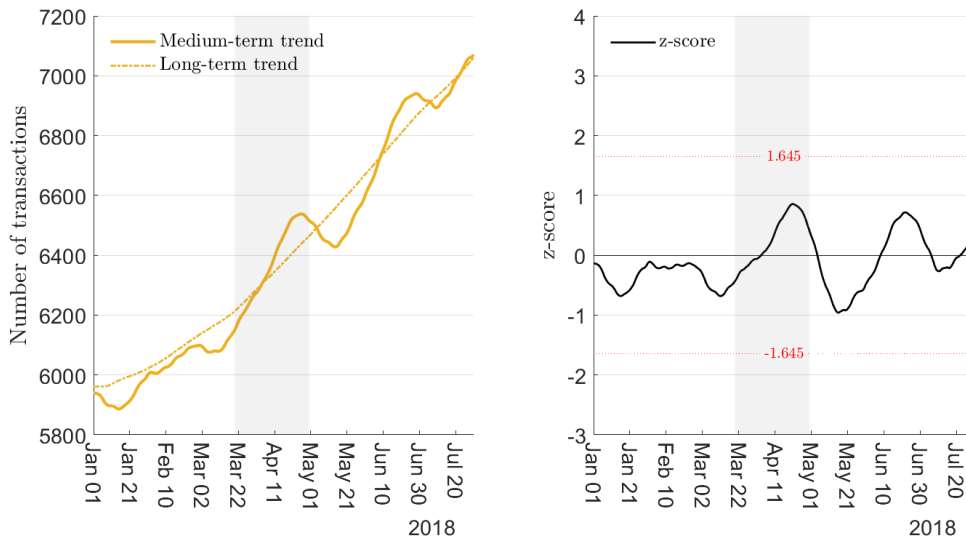
Figure B4: Representative Examples of Crunch and Non-crunch Districts

Number of Transactions and Z-scores

(a) Crunch district (Hyderabad – Telangana)
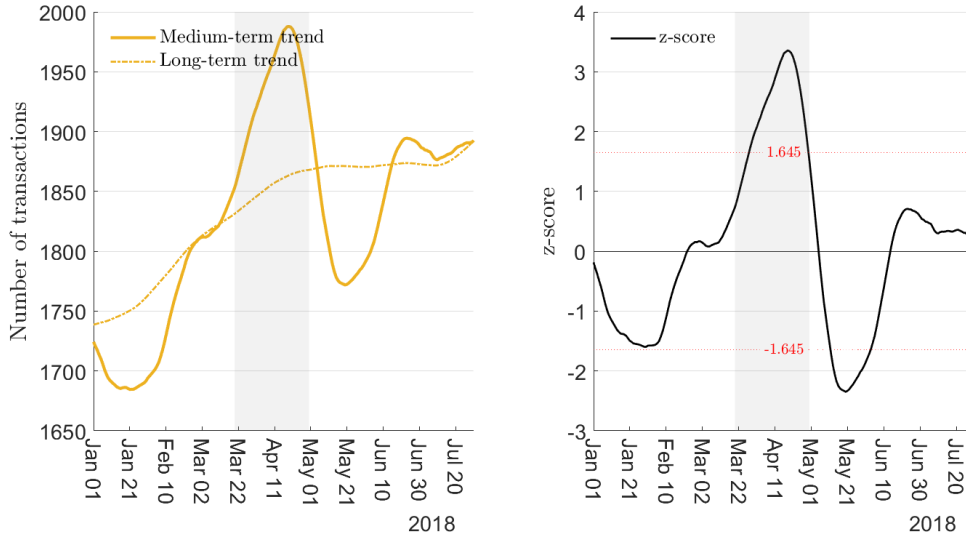
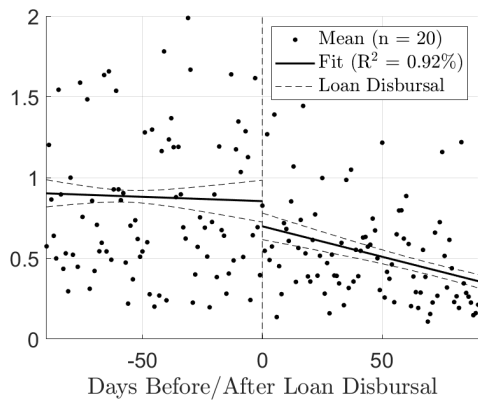### (b) Non-crunch district (Pune – Maharashtra)

Left panels plot the daily number of transactions aggregated over all the merchants in the district. The daily medium term trend plots for a day the mean estimated using Epanechnikov Kernel weights, over a two-month window centered around that day (one month of data on either side of the date). The daily long-term trend plots for a day the mean estimated using Epanechnikov Kernel weights, over a six-month bandwidth centered around that day (3 months of data on either side of the date). The right panels plot the z-score for the district which is normalized the deviation of the deviation of the medium-term trend value from the long-term trend value. Districts with the maximum normalized deviation above 1.645 in the period 20 March - 30 April, 2018 are classified as cash crunch districts.

Cash Crunch and Sales Around Disbursal: 90-day Window

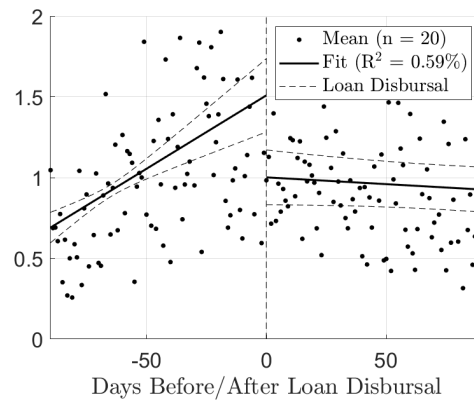Figure B5: Cash Crunch and Borrowing Merchants' Sales Pre- and Post- Loan Disbursal

Transaction Value (normalized,90-day window)
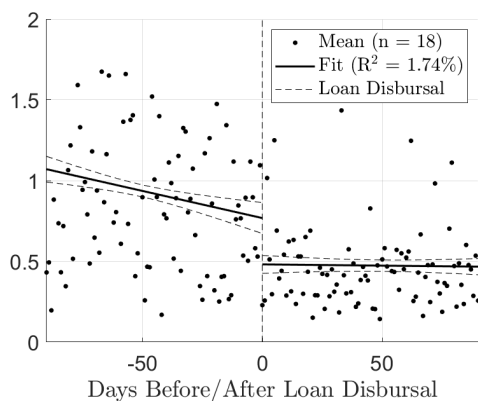
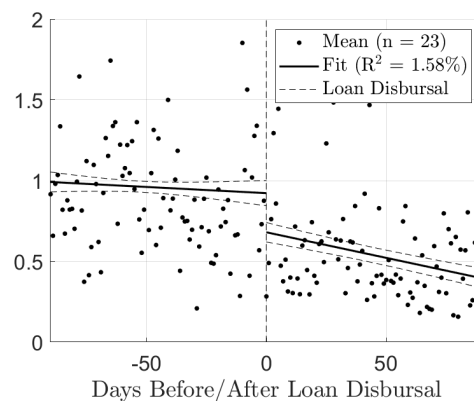Crunch Period, Mar 20 – Apr 30, 2018

(a) Crunch Districts

(b) Non-crunch Districts

Non-crunch Periods, Oct 1 – Dec 31, 2017 & Jun 1 – Jul 31, 2018

(c) Crunch Districts

(d) Non-crunch Districts

Points on the graphs represent mean of the normalized daily transaction values, over merchants. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*Pre disbursal long term average sales*). On the horizontal axis, 0 represents the day of disbursal and negative integers refer to days before disbursal and positive integers to days after disbursal. Solid lines represent the fit by a local regression for a 90-day window around disbursal. Dashed lines show 95% confidence interval using standard errors clustered by loan. *n* in the legend refers to number of loans (number of borrowers). Samples consist of only non-performing repeat loans. For the 90-day bandwidth, only those repeat loans are considered that were disbursed more than 7 days 90 days after the closure of the previous loan of the borrower. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. Table B7 in Appendix B gives the classification of districts as crunch and non-crunch districts.

Appendix C   Robustness Checks

C.1   Alternative Estimation Windows

Table C8: Performing vs. Non-Performing Loans

Dependent Variable: Daily Transaction Value (normalized, 14-day window)

| | All | Performing Loans | | | Non-performing Loans | | |
| | Brwrs. | Non-rep. | Repeat Borrowers | | Non-rep. | Repeat Borrowers | |
	& Loans	Brwrs.	1st Loan	Rep. Loan	Brwrs.	1st Loan	Rep. Loan
Intercept	**1.08*****	**1.16*****	**1.18*****	**1.19*****	**0.84*****	**0.82*****	**0.94*****
	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)
$(1-\mathbb{D}) \times$ day	-2.5E-03	-4.8E-03	-2.3E-03	-1.1E-03	**-0.01****	-9.7E-05	3.9E-03
	(1.8E-03)	(5.0E-03)	(3.2E-03)	(3.7E-03)	(4.7E-03)	(4.7E-03)	(5.0E-03)
Discontinuity, $\mathbb{D}$	**-0.06*****	-0.03	-0.05	-0.06	-0.05	-7.9E-03	**-0.11****
	(0.02)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
$\mathbb{D} \times$ day	2.0E-03	-2.5E-03	**9.3E-03*****	**8.0E-03****	**-8.2E-03****	-3.4E-03	**-0.01*****
	(1.5E-03)	(4.1E-03)	(2.8E-03)	(3.4E-03)	(3.7E-03)	(4.4E-03)	(3.7E-03)
No. Loans	8,480	1,112	2,594	2,110	1,040	613	1,011
No. Obs.	245,920	32,248	75,226	61,190	30,160	17,777	29,319
R^2	0.02%	0.03%	0.02%	0.01%	0.24%	0.01%	0.16%
$\bar{R}^2$	0.02%	0.02%	0.01%	0.01%	0.22%	-0.01%	0.15%
Bandwidth (h)	14	14	14	14	14	14	14
Cutoff	0	0	0	0	0	0	0

Results from local regression of merchants' normalized daily transaction value as dependent variable. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). Regression uses number of days since loan disbursal (day) as running variable. Day number centred around day of loan disbursal, such that day $= 0$ for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{D}$ is a dummy variable that takes value 1 if day ≥ 0 and 0 otherwise. Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 30 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall $> 5\%$ of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Local regression is performed using a box kernel, over a 14-day bandwidth. Number of polynomial terms on each side of cut-off correspond to the specification with the lowest BIC.
Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table C9: Performing vs. Non-Performing Loans

Dependent Variable: Daily Transaction Value (normalized, 30-day window)

	All	Performing Loans			Non-performing Loans		
	Brwrs.	Non-rep.	Repeat Borrowers		Non-rep.	Repeat Borrowers	
	& Loans	Brwrs.	1st Loan	Rep. Loan	Brwrs.	1st Loan	Rep. Loan
Intercept	**1.05*****	**1.20*****	**1.13*****	**1.23*****	**0.85*****	**0.79*****	**0.90*****
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
$(1-\mathbb{D}) \times$ day	**-9.7E-03*****	2.1E-04	**-0.01*****	**5.0E-03*****	**-8.7E-03*****	**-4.0E-03****	1.2E-03
	(2.5E-03)	(1.8E-03)	(4.4E-03)	(1.6E-03)	(1.8E-03)	(1.7E-03)	(2.0E-03)
$(1-\mathbb{D}) \times (\text{day})^2$	**-2.9E-04*****		**-4.5E-04*****				
	(7.9E-05)		(1.4E-04)				
Discontinuity, $\mathbb{D}$	-7.5E-03	**-0.07****	0.03	**-0.10****	**-0.06****	0.05	**-0.11****
	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
$\mathbb{D} \times$ day	**-1.3E-03****	-1.8E-03	**3.4E-03*****	**3.1E-03****	**-8.7E-03*****	**-9.1E-03*****	**-8.6E-03*****
	(5.6E-04)	(1.4E-03)	(1.0E-03)	(1.5E-03)	(1.2E-03)	(1.3E-03)	(1.5E-03)
No. Loans	7,217	1,112	2,594	1,219	1,040	613	639
No. Obs.	440,237	67,832	158,234	74,359	63,440	37,393	38,979
R^2	0.04%	0.04%	0.02%	0.02%	0.77%	0.36%	0.40%
$\bar{R}^2$	0.04%	0.04%	0.01%	0.02%	0.76%	0.34%	0.39%
Bandwidth (h)	30	30	30	30	30	30	30
Cutoff	0	0	0	0	0	0	0

Results from local regression of merchants' normalized daily transaction value as dependent variable. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). Regression uses number of days since loan disbursal (day) as running variable. Day number centred around day of loan disbursal, such that day $= 0$ for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{D}$ is a dummy variable that takes value 1 if day ≥ 0 and 0 otherwise. Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 30 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall $> 5\%$ of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Local regression is performed using a box kernel, over a 30-day bandwidth. Number of polynomial terms on each side of cut-off correspond to the specification with the lowest BIC.
Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table C10: Performing vs. Non-Performing Loans

Dependent Variable: Daily Transaction Value (normalized, 90-day window)

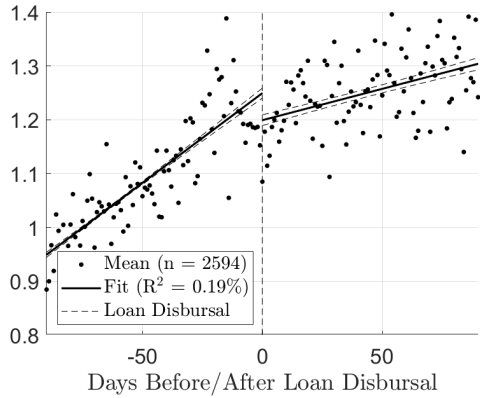|	All	Performing Loans			Non-performing Loans		
	Brwrs.	Non-rep.	Repeat Borrowers		Non-rep.	Repeat Borrowers	
	& Loans	Brwrs.	1st Loan	Rep. Loan	Brwrs.	1st Loan	Rep. Loan
Intercept	1.11***	1.25***	1.25***	1.16***	0.87***	0.75***	0.89***
	(0.01)	(0.02)	(0.01)	(0.04)	(0.03)	(0.03)	(0.05)
$(1-\mathbb{D}) \times \text{day}$	-2.0E-04	3.4E-03***	3.3E-03***	3.0E-03***	-8.2E-03***	-8.0E-03***	-6.3E-04
	(5.3E-04)	(3.5E-04)	(2.2E-04)	(6.2E-04)	(1.3E-03)	(1.4E-03)	(9.0E-04)
$(1-\mathbb{D}) \times (\text{day})^2$	-2.2E-05***				-8.3E-05***	-5.7E-05***	
	(5.4E-06)				(1.3E-05)	(1.5E-05)	
Discontinuity, $\mathbb{D}$	-0.08***	-0.14***	-0.05***	0.02	-0.08***	0.05	-0.18***
	(0.01)	(0.02)	(0.02)	(0.05)	(0.03)	(0.04)	(0.05)
$\mathbb{D} \times \text{day}$	-8.0E-04***	-7.1E-04**	1.2E-03***	5.9E-04	-9.9E-03***	-7.4E-03***	-2.5E-03***
	(1.5E-04)	(3.6E-04)	(2.5E-04)	(6.9E-04)	(9.5E-04)	(1.1E-03)	(5.3E-04)
$\mathbb{D} \times (\text{day})^2$					5.1E-05***	6.2E-05***	
					(9.6E-06)	(1.1E-05)	
No. Loans	6,066	1,112	2,594	429	1,040	613	278
No. Obs.	1,096,193	200,987	468,877	77,400	188,089	110,699	50,141
R^2	0.05%	0.09%	0.19%	0.19%	2.35%	1.03%	0.77%
$\bar{R}^2$	0.05%	0.09%	0.19%	0.19%	2.34%	1.03%	0.76%
Bandwidth (h)	90	90	90	90	90	90	90
Cutoff	0	0	0	0	0	0	0

Results from local regression of merchants' normalized daily transaction value as dependent variable. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). Regression uses number of days since loan disbursal (day) as running variable. Day number centred around day of loan disbursal, such that day = 0 for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{D}$ is a dummy variable that takes value 1 if day $\geq$ 0 and 0 otherwise. Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 90 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. For detailed definitions of samples see Table A1. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Local regression is performed using a box kernel, over a 90-day bandwidth. Number of polynomial terms on each side of cut-off correspond to the specification with the lowest BIC.
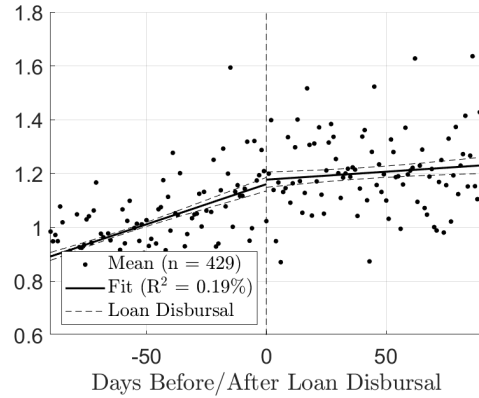
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Figure C6: Merchants' Normalized Transaction Value Pre- and Post- Loan Disbursal

90-day window

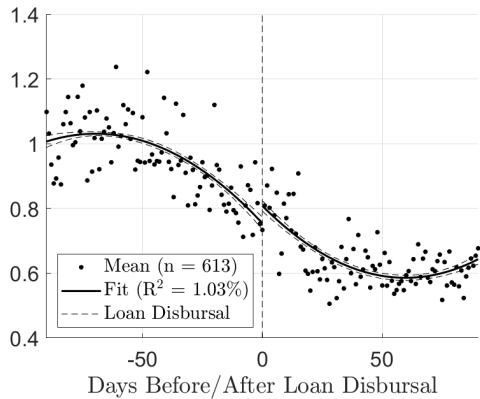### Performing Loans, Repeat Borrowers
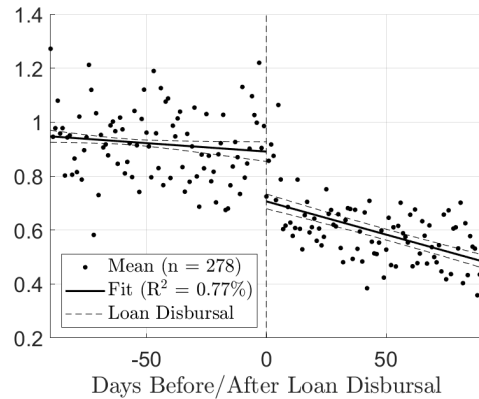

(a) 1st Loan

(b) Repeat Loans

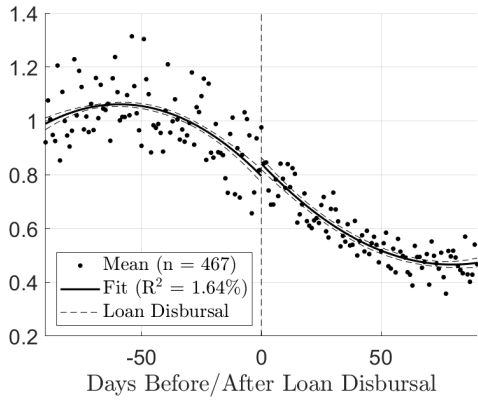### Non-performing Loans, Repeat Borrowers
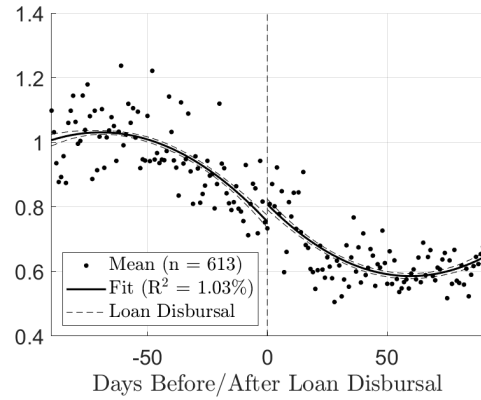

(c) 1st Loan

(d) Repeat Loans

Points on the graphs represent mean of the normalized daily transaction values, over merchants. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). On the horizontal axis, 0 represents the day of disbursal and negative integers refer to days before disbursal and positive integers to days after disbursal. Solid lines represent the fit by a local regression for a 90-day window around disbursal. Dashed lines show 95% confidence interval using standard errors clustered by loan. Dashed vertical line shows date of loan disbursal. n in the legend refers to number of loans (number of borrowers). Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 90 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. For detailed definitions of samples see Table A1.

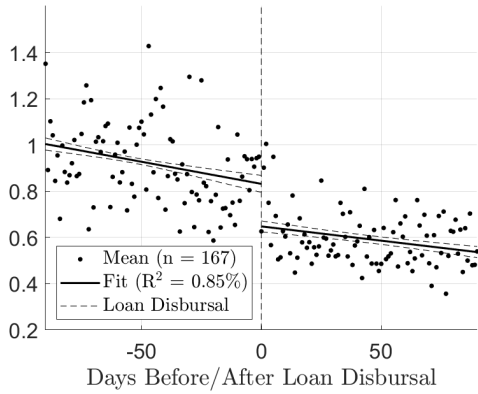## Figure C7: Merchants' Normalized Transaction Value Pre- and Post- Loan Disbursal

Late Loans, 90-day window
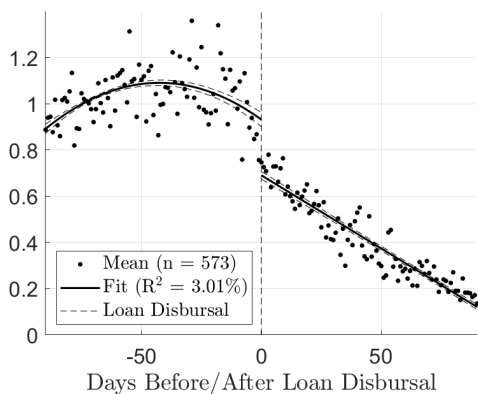

(a) Non-Repeat Borrowers
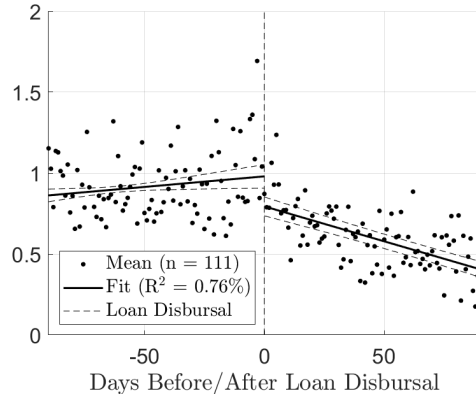

(b) Repeat Borrowers, 1st Loan

(c) Repeat Borrowers, Repeat Loan

Default Loans, 90-day window

(d) Non-Repeat Borrowers

(e) Repeat Borrowers, Repeat Loan

Late loans are those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan. Default loans are loans with a shortfall > 5% of repayment amount which were either closed by the lender (written off) or still pending as of end 2019. n in the legend refers to number of loans (number of borrowers). For more details see notes for Figure C6 and for detailed definitions of samples see Table A1.

C.2 Robustness Check Across Month of Disbursal

Table C11: Non-Performing Repeat Loans Excluding Particular Months

Dependent Variable: Daily Transaction Value (normalized, 7-day window)

	Oct - Dec, 2017			Jan - Apr, 2018			
	Oct	Nov[a]	Dec	Jan	Feb	Mar	Apr
Intercept	1.02***	-	1.01***	1.00***	1.02***	1.00***	1.00***
	(0.06)		(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
$(1 - \mathbb{D}) \times$ day	0.02	-	0.02	0.02	0.02	9.4E-03	0.01
	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Discontinuity, $\mathbb{D}$	-0.19***	-	-0.18***	-0.17**	-0.18**	-0.19**	-0.17**
	(0.07)		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$\mathbb{D} \times$ day	-4.2E-03	-	-4.2E-03	-6.4E-03	-6.8E-03	-1.2E-03	-7.0E-03
	(9.3E-03)		(9.1E-03)	(9.6E-03)	(9.5E-03)	(9.6E-03)	(9.4E-03)
No. Loans	1,201	-	1,216	1,130	1,091	1,102	1,121
No. Obs.	18,015	-	18,240	16,950	16,365	16,530	16,815
R^2	0.10%	-	0.10%	0.09%	0.10%	0.12%	0.10%
$\bar{R}^2$	0.08%	-	0.08%	0.07%	0.08%	0.10%	0.08%
Bandwidth (h)	7	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0	0

|	May - Nov, 2018						
	May	Jun	Jul	Aug	Sep	Oct	Nov
Intercept	1.01***	0.99***	1.00***	1.02***	1.01***	1.03***	1.02***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
$(1 - \mathbb{D}) \times$ day	0.02	9.4E-03	0.02	0.01	0.01	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Discontinuity, $\mathbb{D}$	-0.18**	-0.16**	-0.19***	-0.18**	-0.18**	-0.21***	-0.19**
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$\mathbb{D} \times$ day	-5.6E-03	1.1E-04	-1.6E-03	-4.5E-03	-3.7E-03	-1.6E-03	-2.6E-03
	(9.4E-03)	(9.9E-03)	(8.8E-03)	(9.4E-03)	(9.4E-03)	(9.4E-03)	(0.01)
No. Loans	1,157	1,066	1,171	1,165	1,178	1,146	1,034
No. Obs.	17,355	15,990	17,565	17,475	17,670	17,190	15,510
R^2	0.09%	0.08%	0.09%	0.10%	0.10%	0.10%	0.09%
$\bar{R}^2$	0.07%	0.05%	0.07%	0.08%	0.08%	0.08%	0.07%
Bandwidth (h)	7	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0	0

Regression sample includes only repeat non-performing loans but excluding the loans disbursed in the month indicated. Dependent variable is the normalized daily transaction value of the borrowing merchant. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average*). Regression uses number of days since loan disbursal (day) as running variable. Day number centred around day of loan disbursal, such that day $= 0$ for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{D}$ is a dummy variable that takes value 1 if day ≥ 0 and 0 otherwise. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 7 days after the closure of the preceding loan of the borrower. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. All loans have 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Local (linear) regression is performed using a box kernel, over a 7-day bandwidth.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
[a] There was only one loan disbursed in Nov 2017 and that was a performing loan. Therefore, this procedure does not exclude any loan for Nov 2017 and the results remain the same as for the overall sample of non-performing repeat loans in Table 6.
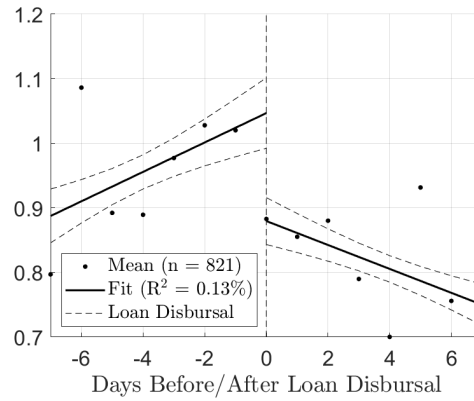
C.3   Ruling Out Aggregate Shock

Figure C8: Merchants' Normalized Transaction Value Pre- and Post- Loan Disbursal

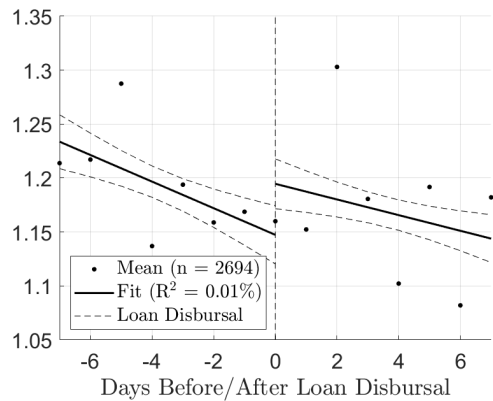First vs. Repeat Non-Performing Loans With Common Dates of Disbursal
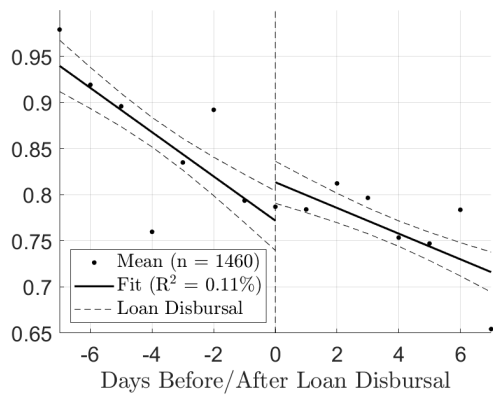
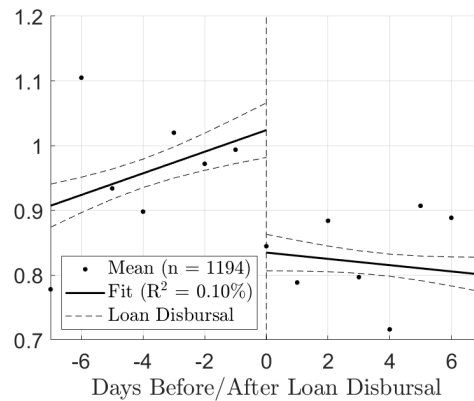(a) Non-repeat and Repeat Borrowers, 1st Loan

(b) Repeat Borrowers, Repeat Loan

Perf. vs. Non-Perf. Repeat Loans With Common Dates of Disbursal

(c) Performing Loan

(d) Non-Performing Loan

First half of the figure compares non-performing first loan (either of the non-repeat borrowers or of the repeat borrowers) with the non-performing repeat loans that share common date of disbursal. Second half of the figure compares performing repeat loans with non-performing repeat loans that share common date of disbursal. Repeat loans include second and subsequent loans. Only those repeat loans are considered that were disbursed more than 7 days after the closure of the preceding loan of the borrower. n in the legend refers to number of loans (number of borrowers). Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. For detailed notes see Figure 3.

Table C12: Loans with Common Disbursal Dates

Dependent Variable: Merchants' Daily Transaction Value (normalized, 7-day and 90-day window)

	7-day Estimation Window				90-day Estimation Window			
	Non-performing Loan		Repeat Loan		Non-performing Loan		Repeat Loan	
	1st Loan	Repeat Loan	Perf. Loan	Non-perf. Loan	1st Loan	Repeat Loan	Perf. Loan	Non-perf. Loan
Intercept	0.77***	1.05***	1.15***	1.02***	0.83***	0.85***	1.16***	0.89***
	(0.05)	(0.08)	(0.04)	(0.06)	(0.02)	(0.07)	(0.04)	(0.06)
$(1-\mathbb{1}) \times$ day	-0.02**	0.02	-0.01	0.02	-7.5E-03***	-1.5E-03	2.9E-03***	-5.7E-04
	(0.01)	(0.02)	(9.2E-03)	(0.01)	(1.0E-03)	(1.2E-03)	(6.3E-04)	(9.1E-04)
$(1-\mathbb{1}) \times (\text{day})^2$					-6.6E-05***			
					(1.1E-05)			
Discontinuity, $\mathbb{1}$	0.04	-0.17*	0.05	-0.19***	-0.03	-0.10*	0.01	-0.18***
	(0.06)	(0.09)	(0.05)	(0.07)	(0.02)	(0.06)	(0.05)	(0.05)
$\mathbb{1} \times$ day	-0.01*	-0.02	-7.3E-03	-4.8E-03	-9.1E-03***	-2.8E-03***	7.0E-04	-2.5E-03***
	(7.4E-03)	(0.01)	(7.5E-03)	(9.2E-03)	(7.7E-04)	(7.3E-04)	(7.0E-04)	(5.4E-04)
$\mathbb{1} \times (\text{day})^2$					5.6E-05***			
					(7.8E-06)			
No. Loans	1,460	821	2,694	1,194	1,460	166	418	273
No. Obs.	21,900	12,315	40,410	17,910	263,898	29,980	75,409	49,236
R^2	0.11%	0.13%	0.01%	0.10%	1.80%	0.60%	0.19%	0.76%
$\bar{R}^2$	0.09%	0.10%	0.00%	0.08%	1.80%	0.59%	0.18%	0.75%
Bandwidth (h)	7	7	7	7	90	90	90	90
Cutoff	0	0	0	0	0	0	0	0

Results from local regression of merchants' normalized daily transaction value as dependent variable. Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average*). Repeat borrowers are merchants who took at least two loans from the lender. Repeat loans include second and subsequent loans. For the 7-day bandwidth (90-day bandwidth), only those repeat loans are considered that were disbursed more than 7 days (90 days) after the closure of the previous loan of the borrower. Regression uses number of days since loan disbursal (day) as running variable. Day number centred around day of loan disbursal, such that day = 0 for disbursal date and day > 0 for days after disbursal, and negative otherwise. $\mathbb{1}$ is a dummy variable that takes value 1 if day $\geq$ 0 and 0 otherwise. Non-performing loans are either defaulting or late loans. For detailed definitions of samples see Table A1. All samples include loans disbursed between October 2017 and November 2018, and with 90-day or 180-day suggested maturity. Standard errors are clustered by loan and given in parentheses. Number of polynomial terms on each side of cut-off correspond to the specification with the lowest BIC. Within each estimation window, first pair of results compare non-performing first loan (either of the non-repeat borrowers or of the repeat borrowers) with the non-performing repeat loans that share common date of disbursal. Second pair of results compare performing repeat loans with non-performing repeat loans that share common date of disbursal.
Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.4 Ruling Out Seasonality as an Alternative Explanation

Another alternative explanation for the observed discontinuity is that it is the result of seasonal effects. Indeed, merchants' individual data show weekly seasonality, with more transactions happening over the weekends. Suppose the hypothetical case that all loans were disbursed on Mondays. Then, the observed drop in sales on the day of disbursal will simply reflect the seasonal effect of the difference between weekends (the days preceding disbursals) and weekdays (the days after disbursals). Because loans were disbursed on different weekdays, one could (bluntly) argue that merchants' individual weekly seasonality would be smoothed out in the aggregate. However, we still need to worry about it. The reason is that the distribution of the disbursal days over the days of the week is not uniform; there were fewer loans disbursed on Saturdays than during the working week, and no loans were disbursed on Sundays. As a consequence of this non-uniform distribution, the distribution of covered weekdays differs across different days since disbursal. This results in a seasonality also in the aggregated time series, despite the overlap of the individual seasonal effects in the aggregated series. To illustrate the mechanism, suppose, for simplicity, no loan was disbursed over the weekend, and all loans were evenly disbursed over the working week. Recall that our merchants transact more over the weekend (Saturday - Sunday) than on weekdays (Monday - Friday). Now, the aggregate of sales over merchants, made on the day of disbursal ($\text{day} = 0$) will include transactions made only on weekdays but no transactions made on the high-sales weekend. The subsequent day, though, ($\text{day} = 1$), will include transactions on Tuesdays through Fridays and also from Saturdays. That is, the aggregate will also include transactions on one of the high-sales weekend days. The aggregates sales on $\text{day} = 2, 3, 4, 5$ will also include transactions made on Saturdays and Sundays, and, hence, include even more high-sales weekend days. Similarly, for aggregate sales on $\text{day} = 6$ we will include, in addition to other days, only Sunday. For aggregate transaction on $\text{day} = 7$, again, we will include no weekend-day transactions. Similarly, the day before disbursal, $\text{day} = -1$, will include Sunday of the weekend transactions, and the preceding days $\text{day} = -5, -4, -3, -2$ will include both weekend days.

To control for these seasonal effects, following the suggestion of Hausman and Rapson (2018), we first regress the daily normalized sales against the *day-of-the-week* dummies and obtain the residuals. As a second step, we perform the same regression as before, but now $\text{esales}_{i,t}$ is the residual of the normalized transaction value. The results, presented in Table C13, are very close to the baseline results, indicating that such seasonal variations have no effects on our results.

Table C13: Merchants' Sales Around Disbursal: Performing vs. Non-Performing Loans

Dependent Variable: Residuals of Daily Transactions Value (normalized, 7-day window)

	All	Performing Loans			Non-performing Loans		
	Brwrs.	Non-rep.	Repeat Borrowers		Non-rep.	Repeat Borrowers	
	& Loans	Brwrs.	1st Loan	Rep. Loan	Brwrs.	1st Loan	Rep. Loan
Intercept	1.1E-03	-0.07	-0.02	1.5E-03	-0.05	-0.02	**0.17*****
	(0.02)	(0.06)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
$(1-\mathbb{D}) \times$ day	**-0.02*****	**-0.05*****	**-0.01***	**-0.02***	**-0.05*****	-5.9E-03	0.01
	(4.7E-03)	(0.02)	(8.7E-03)	(8.7E-03)	(0.01)	(0.01)	(0.01)
Discontinuity, $\mathbb{D}$	0.04	**0.21*****	0.02	0.06	0.09	0.02	**-0.17****
	(0.02)	(0.07)	(0.05)	(0.05)	(0.07)	(0.07)	(0.07)
$\mathbb{D} \times$ day	-5.0E-03	**-0.03*****	9.0E-03	-6.2E-03	**-0.02***	-6.8E-03	-3.0E-03
	(3.6E-03)	(9.9E-03)	(6.8E-03)	(7.3E-03)	(9.2E-03)	(0.01)	(9.2E-03)
No. Loans	9,327	1,112	2,594	2,752	1,040	613	1,216
No. Obs.	139,905	16,680	38,910	41,280	15,600	9,195	18,240
R^2	0.03%	0.17%	0.01%	0.01%	0.25%	0.01%	0.10%
$\bar{R}^2$	0.03%	0.14%	0.00%	0.00%	0.23%	-0.03%	0.07%
Bandwidth (h)	7	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0	0

Results from local regression of merchants' residuals of normalized daily transaction value as dependent variable. Residuals are obtained by regressing normalized daily transaction value on day-of-the-week dummies following Hausman and Rapson (2018). Daily transaction values are normalized by the merchant's average daily transaction value calculated in the 90-day period between 119 days and 30 days before loan disbursal (*pre-disbursal long-term average sales*). Regression uses number of days since loan disbursal (day) as running variable. For detailed notes on regressions see Table 6. For detailed definitions of samples see Table A1.

Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$