Fintech Lending and Sales Manipulation

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WWZ

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Summary.

Problem. Challenging debt enforcement given weak institutions hampers lending to Micro and SME.

Solution. Fintech payments companies lending to merchants: Location in payments chain allows automatic deduction of repayment at source before borrowing merchants receive sales proceeds.

Examples. Paypal, Square, Ant Fin., many more acting as lenders.

Analysis. Use transaction data from an Indian Fintech payments processor, offering such loans with automatic, sales-linked repayment. Analysis of merchants' electronic sales pre and post loan disbursal.

General Result. Borrowing merchants discontinuously reduce electronic sales processed through the processor right after loan disbursal, potentially diverting to other means of payments.

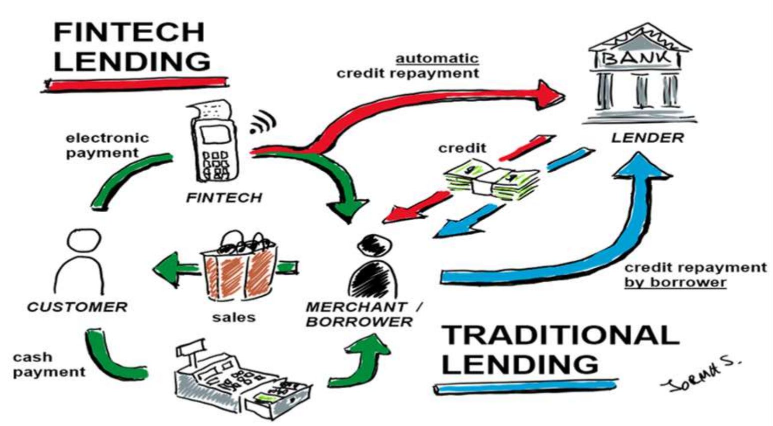
- **Result #1.** Diversion of electronic sales to intentionally default or delay repayment.
- **Result #2.** Higher incidence of manipulation for merchants with better credit scores and hence better outside opportunities
- **Result #3.** Evidence for merchants diverting electronic sales to cash, using the 2018 cash crunch episode.

Conclusion. Competition from cash and other lenders limit the effectiveness of this enforcement technology

Institutional Setup of Fintech Lending.

Traditional Lending. Lender grants credit to merchant. Loan repayment following predetermined amortization plan by merchant.

Fintech Lending. Lender/Payments Company grants credit. Loan repayment by automatic deduction of a proportion of merchant's electronic sales proceeds



Average Loan Size. ~34,000 INR (~550 USD)

Average Daily Transaction. ~4,000 INR (~65 USD)

Avg. Number of Transactions. ~2.8 per day

Average Tenure. ~130 days

Interest Rate. 2% per month.

Methods.

Quantifying Discontinuity in Sales. Use regression discontinuity design and fit local regressions in narrow window ($h = 7$ days) around date of loan disbursal ($day_{i,t} = 0$). Regress days after disbursal ($day_{i,t}$) on merchant i's sales ($esales_{i,t}$) on date t. Inclusion of dummy variable $\mathbb{D}$ for post-disbursal days ($day_{i,t} \geq 0$) allows to interpret corresponding coefficient, τ, as the magnitude of the drop in sales on the day of disbursal.

$$\min_{\alpha,\tau,\beta_s,\gamma_s} \sum_{i=1}^{n}\sum_{t\in T} \mathbb{1}\{|\mathrm{day}_{i,t}| \le h\}\Big[\mathrm{esales}_{i,t} - \alpha - \tau \times \mathbb{D}_{i,t} - \sum_{s=1}^{p}\left(\beta_s \times (1-\mathbb{D}_{i,t}) \times (\mathrm{day}_{i,t})^s\right) - \sum_{s=1}^{q}\left(\gamma_s \times \mathbb{D}_{i,t} \times (\mathrm{day}_{i,t})^s\right)\Big]^2,$$

Selection of polynomial based on BIC (Hausman, Rapson 2018).

Normalization of Transaction Value. Sales variable $esales_{i,t}$ is total daily electronic transaction value divided by average daily value 120 to 30 day before loan disbursal.

Robustness Checks.

- **No weekday effect.** Robust results after we re-perform analysis after extracting residuals by controlling for weekday effects (Hausman, Rapson, 2018)
- **No aggregate shock.** Compare repeat and non-performing with non-repeat and performing loans issued on same dates to rule out discontinuity being the result of an aggregate shock.
- **No specific shock.** Results not driven by particular month.
- **Check alternative Estimation Windows.** Results robust to alternative estimation windows (14, 30, 90 days).

Results.

Result #1. Non-performing, repeat borrowers exhibit larger discontinuity, pointing towards diversion of electronic sales to intentionally default.

→ **Stop transacting via payments company to default or delay repayment**
→ **Learning effect**

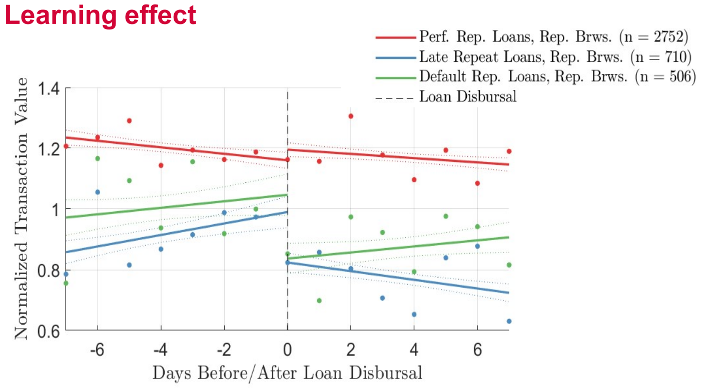


Table 7: Late vs. Default Non-Performing Loans

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

	Late Loans			Default Loans	
	Non-repeat	Repeat Borrowers			
	Brwrs.	1st Loan	Repeat Loan	1st Loan	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 those loans that were closed (not followed up any more) by the lender and had a shortfall > 5% of repayment amount. These loans were written off. For detailed definitions of samples see Table A1. For detailed notes on regressions see Table 6.
Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Result #2. Non-perf., repeat borrowers with better credit scores, show higher incidence of manipulation. We relate this to their better outside opportunities, i.e., access to alternative credit sources.(Note that lender does not report to credit bureau)

→ **Competition in lending**

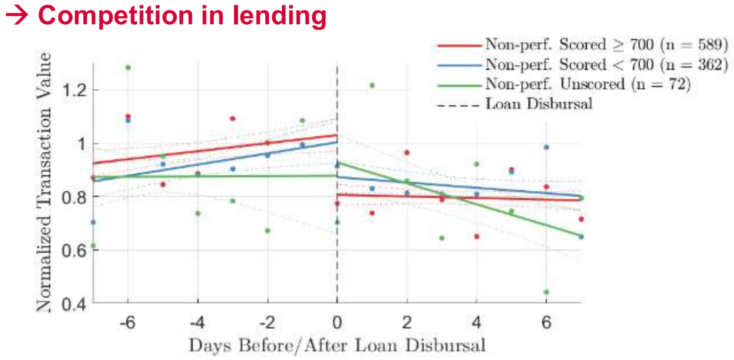


Table 8: Performing and Non-performing Repeat Loans by Credit Score

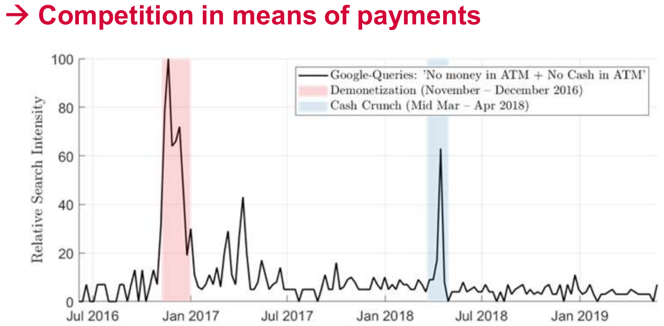
Dependent Variable: Daily Transaction Value (normalized, 7-day window)

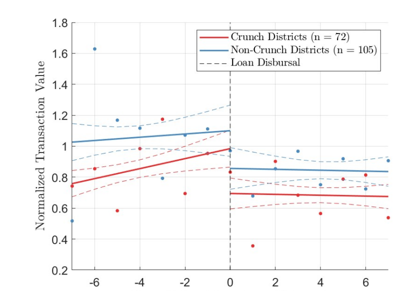
	Performing, Repeat Loan			Non-performing, Repeat Loan			Default, Repeat Loan		
	≥ 700	< 700	Unscored	≥ 700	< 700	Unscored	≥ 700	< 700	Unscored
Intercept	**1.10*****	**1.33*****	**0.85*****	**1.03*****	**1.00*****	**0.88*****	**1.25*****	**0.86*****	**0.59*****
	(0.06)	(0.08)	(0.13)	(0.09)	(0.12)	(0.32)	(0.19)	(0.13)	(0.20)
$(1-\mathbb{D}) \times$ day	**-0.03****	**0.03****	**-0.10*****	0.01	0.02	5.9E-04	0.04	-7.9E-03	**-0.08***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.06)	(0.04)	(0.03)	(0.05)
Discontinuity, $\mathbb{D}$	0.11	**-0.18***	**0.44****	**-0.22****	-0.13	0.05	**-0.40****	-0.02	0.20
	(0.07)	(0.10)	(0.18)	(0.10)	(0.14)	(0.24)	(0.20)	(0.20)	(0.27)
$\mathbb{D} \times$ day	-7.0E-03	-6.2E-03	0.01	-3.0E-03	-1.0E-02	-0.04	-2.9E-03	0.01	0.02
	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.07)
No. Loans	1,408	663	228	589	362	72	225	176	28
No. Obs.	21,120	9,945	3,420	8,835	5,430	1,080	3,375	2,640	420
R^2	0.03%	0.06%	0.25%	0.15%	0.05%	0.16%	0.24%	0.01%	0.64%
$\bar{R}^2$	0.01%	0.02%	0.13%	0.11%	-0.03%	-0.22%	0.12%	-0.14%	-0.32%
Bandwidth (h)	7	7	7	7	7	7	7	7	7
Cutoff	0	0	0	0	0	0	0	0	0

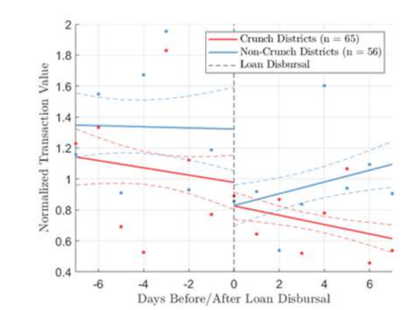
Regression samples include only repeat loans (second and subsequent loans), and only those that were disbursed more than 7 days after the closure of the previous loan of the borrower. Credit scores correspond to that of the merchant owning the business to which the loan was disbursed. Credit scores range 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 (those non-defaulting loans that took more than 30 days than the implied tenure to fully repay the loan.).For detailed definitions of samples see Table A1. For detailed notes on regressions see Table 6.
Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Result #3. During Mar – Apr 2018 shortage of cash (cash crunch) in some Indian districts. Cash shortage constrains merchants discretion to divert sales to cash.
Borrowing merchants in crunch districts no longer show discontinuity during crunch period – compared to merchants from non-crunch districts and non-crunch periods. Evidence for diversion of electronic sales to cash.

→ **Competition in means of payments**







Conclusion.

Potential. Seniority of lender achieved by payment companies lending has potential to strengthen debt enforcement and ease access to unbanked MSME.

Limitations. Ability to manipulate and divert sales constraints enforcement technology. Though move towards digital payments could mitigate possibilities for manipulation.

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