Resilience of the Group Lending Model to a COVID-19 Induced Shock: Evidence from an Indian Microfinance Fund

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ABSTRACT: We study the effect of an exogenous shock in the form of Coronavirus lock-downs on individual default, and on default contagion within the microfinance (MF) sector in India. We rely on proprietary data obtained from a MF institution for the period from Nov 2019 to Dec 2020. We show that default increased to 95.29% in the month of April 2020 when Covid lockdowns were fully in place. However, borrowers bounced back almost immediately thereafter, either making full or partial payments, so that defaults had fallen to 5.92% by December 2020. We show that the group lending model helped blunt the impact of the exogenous covid shock on rates of default among the majority (92%) of borrowers who are residents of rural districts. In results new to the MF literature, we show an absence of contagion from groups in villages with the highest defaults to other groups in the same district as the distressed village. We conclude that MF sector can absorb exogenous shocks like the pandemic to continue to provide poverty alleviation during difficult times.

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Introduction

The Indian government, like many governments around the world, responded to the Novel Coronavirus pandemic by imposing a lockdown to restrict non-essential activities, travel outside the home, and commerce. Starting with a three-week period that began on March 24th, 2020, the lock-down was extended in two-week increments, until most restrictions on movement were lifted on June 8, 2020. The focus of our study is to determine the robustness of the microfinance (MF) sector to an exogenous adverse shock created by the pandemic. Specifically, we address the risk of default and the level of default contagion within this sector. We seek to identify loan and borrower characteristics that affect the ability of borrowers to repay their loans when faced with the shock. In addition, we determine the level of default contagion from one distressed borrower to other borrowers in the same region.

The 'group lending' model underpins lending in the MF sector. Potential borrowers are invited to form groups so that individual responsibility for compliance with the terms of the loan can be replaced by collective responsibility offered by the group. The pioneer in the 'Group Lending Model' is Grameen Bank, which placed borrowers, primarily female, into groups of five. In Grameen's experience, women were receptive to peer-pressure from other members in the group which led to lower rates of default (Cull and Morduch (2017)). Nonetheless, the sector has experienced clusters of default events ever since its recognition by the Reserve Bank of India in 2004 as a distinct source of funding demand (Gillon (2017)). The first default crisis occurred in 2010 in the state of Andhra Pradesh. Crises have erupted periodically thereafter, with the most recent being the 2019 default crisis in the state of Assam.

The group lending model has characteristics that both exacerbate and mitigate default. Risk of individual default is lowered by peer pressure applied to delinquent borrowers who are publicly identified during community meetings set up by loan officers. Todd (2020) reports that peer pressure can take the form of social exclusion of defaulting borrowers from the rest of the group. Peer-pressure seems to have the desired effect as Cull, Demirguc-Kunt and Morduch (2007) document that lenders who use group-based lending do not face higher default rates. Peer pressure may not be adequate, however, when all borrowers in a group are subject to macro-economic shocks or to an exogenous shock such as the Coronavirus lockdowns. Contagion is the phenomenon where default by one borrower has an impact on otherwise healthy borrowers.[3] The risk of contagion is higher when all borrowers in a group are homogenous in terms of their exposure to a macro-economic shock: Ahlin (2009) confirms that borrowers cluster together by risk type when an MF lender allows individuals to select other members in the group. Contagion can also be a significant risk in group lending settings if there is moral hazard: if borrowers in a group expect that others in the group will fail to repay, they can then default as a group (Bond and Ria (2009), Ogden (2011), Paxton et al. (2000)).

We examine default timing data to understand the effect that an exogenous shock like the Coronavirus lockdown had on individual defaults as well as on contagion within the MF sector in India. With proprietary data from an MF institution in India covering the period from Nov 2019 to Dec 2020, we document default rates for a six-month pre-lockdown period and for a six-month post-lockdown period including the period of the lockdown and subsequent re-opening of the economy. We measure the relative contribution of systematic risk factors versus borrower-specific factors driving aggregate default in the pre- and post-lockdown periods. Second, we study the role of group lending on default in this sector. Third, we study whether there is default contagion in this sector, and the effect of the group lending model on contagion during and after the Covid lockdowns.

Our empirical evidence shows that defaults increased significantly to 95.29% during the month of April 2020 when Covid lockdowns were fully in place. However, borrowers bounced back almost immediately thereafter, either making full or partial payments, such that defaults had fallen to 5.92% by December 2020. Furthermore, those borrowers who failed to make the contractual monthly payments in April 2020 made up the shortfall thereafter in two ways: i) by paying more than the contractually required payments in subsequent months, or, ii) by making payments well after the loans had matured. The group lending model does remarkably well in explaining defaults even during Covid lockdowns. Among the majority (92%) of borrowers who are residents of rural districts, the group lending model appears to blunt the impact of the exogenous shock on rates of default. We find the group lending model does less well among younger residents of urban areas who have limited formal schooling, who eventually defaulted on

[3] See Aragon and Strahan (2012), and Brunnermeier (2009). Benzoni, Collin-Dufresne, Goldstein and Helwege (2015), Das, Duffie, Kapadia, and Saita (2007) and Azizpour, Giesecke and Schwenkler (2017) show that a 'frailty' factor better explains the degree of clustering in corporate defaults in the United states.

their loans. Finally, we find there is no transmission of default contagion from one distressed village to other villages in the same district, and state, as the distressed village. Instead, there is stronger evidence that the possible loss of social capital increased peer-pressure on borrowers who lived geographically closer to the distressed villages to repay their loans.

The rest of our paper is organized as follows: In the second section, we discuss the recent literature on the impact of Covid-19 pandemic on the microfinance industry, and on small business, generally. The third section describes the data. In the fourth section, we provide analysis of default. The fifth section has regression evidence, and the sixth section has evidence on contagion. The seventh section has our conclusions.

2. Literature Review: The Impact of Covid-19 Pandemic on Microfinance Industry

Malik et al. (2020) examines the impact of the Covid-19 pandemic on the microfinance industry. They show that the ability of borrowers in Pakistan to pay off their debt decreased significantly after the pandemic began. They find that household income fell by about 90 percent and households' primary immediate concern was to secure food in early April 2020. As a result, 70 percent of the microfinance borrowers were unable to repay their loans in April 2020. They conclude that Covid-19 was a crisis for low-income communities and prescribe that policy reforms are required in times of crises. Dubey and Sirohi (2021) also find that borrowers were in a difficult financial position immediately after the pandemic. They find that the introduction of a moratorium significantly helped borrowers as covid cases increased.

Alibhai, Bessir, and Weis (2021) analyze the impact of COVID-19 on Ethiopian MF institutions and their borrowers. Their results show that MF institutions experienced defaults, but the severity of the impact varied across institutions; urban MF clients were particularly affected by the pandemic. Ermawati et al. (2021) analyze the performance of MF institutions in Indonesia during the pandemic. Their results are consistent with other studies showing a contraction in financing, savings, and in the number of customers, and an increase in non-performing loans. Their results also show a liquidity shortage and a greater risk of loan defaults. They conclude that government's financial support is crucial during a crisis for MF institutions that are highly exposed to business downturns. There are studies on lending to small businesses that reach the same conclusion that external intervention was necessary during the Covid pandemic. Sparks (2021) shows that stimulus packages provided in the United States helped small businesses during the

Pandemic. Amuda (2020) studies the impact of the coronavirus pandemic on small and medium enterprises (SMEs) in Nigeria. He prescribes additional lending be made available to SMEs to prevent a significant number of defaults caused by the Covid-19 pandemic.

The Indian government did not provide a stimulus package to help borrowers. It did however, impose a moratorium on payments in July 2020. Our study will shed light on how well the MF sector in India withstood the Covid shock without direct monetary support from the government. The evidence can help ascertain whether the group lending model has built-in safeguards that mitigate both default and default contagion.

3. Data

Data were obtained from a private MF fund operating in India that started its lending operations in November 2019. Loan officers from the company visit local communities to find borrowers. The first movers among potential borrowers are constituted into groups. These individuals are encouraged to urge their acquaintances to join and complete a five-person group. The typical loan to an individual borrower is a 12-month loan for an amount of INR 25,000 to be repaid in 52 equal weekly installments. The process of collecting payments is manually intensive; a group meeting attended by a loan officer of the company is called once a week at the home of a group member. The loan officer collects the weekly payment, which is usually paid in cash. When a group member fails to make the weekly payment, a discussion ensues among other group members on whether to make up the shortfall. When the group decides to make up the shortfall on behalf of the defaulting member, other members of the group contribute cash into a pool to make up the payment. It is left up to the group to decide how the shortfall is recovered subsequently from the delinquent member. The ability of the lender to receive contractual payments in this manner is strongly dependent on the level of trust and cohesion among the members of the group.

We have data on individual borrowers from Nov 2019 to December 2020, which encompasses the period from March 2020 to June 2020, when Covid lockdowns occurred. Appendix A.1 has a list of variables included in the dataset. Panels A-E of Table 1 have descriptive statistics on the borrowers. Panel A shows that the mean and median age of the borrowers is 37.9 and 37.6 years respectively. Mean annual household income is INR 8401, which falls in the bottom quarter of the population.[4] A typical borrower household has four family members. The median loan size is INR 25,000, while the third quartile value is INR 30,000. The mean and median interest rate on the loans is around 24%, a high rate of interest compared to a one-year Indian government bond rate of 5.7% that prevailed at the start of the sample period. The high rate of interest reflects higher expected rates of default in this sector. Panel B shows that the largest proportion of borrowers resides in the state of Odisha, followed by Assam. These two states are in the Eastern and North-Eastern regions of the country, where the lender has focused its lending operations. Panel C shows that 28.71% (12.15%+16.56%) of borrowers either did not report their educational level, or did not have any formal schooling. A majority (56.42%) had some level of schooling either up to the ninth, or to the tenth grade. 11.77% of borrowers had non-traditional schooling, details of which are unavailable. Panel D shows that over 85.62% of borrowers used the loan proceeds in agriculture related activities. Panel E shows that a majority of borrowers (91.6%) live in districts classified by their state governments as being rural districts.

4. Analysis of defaults

The variables listed in Appendix A.1 can be used to identify the status of the loan every month. We note that even though payments are made weekly, the dataset is compiled monthly. We take the difference between the 'amount due' and the 'amount collected' to classify the loan into six categories: 1) fully paid if the difference between the amount due and collected is zero, 2) partial paid if the difference between the two is greater than zero, 3) overpaid if the difference is less than zero, 4) moratorium if the 'amount due' in a month is zero even though the loan has not matured, 5) paid after due if the difference is less than zero after the maturity date, and finally, 6) default if 'amount collected' is equal to zero even though the loan is active, and the 'amount due' is greater than zero.

Table 2 has the status of loans by number of active loans that fall into each of the six categories. Between 95-97.5% of loans were fully paid up until February 2020, the month before Covid lockdowns started. Starting in March 2020, there is a fall-off in fully paid loans. In March, April and May 2020, fully paid loans dropped to 5.85%, 0.05% and 2.06%, respectively. The proportion of fully paid loans starts to rise in June 2020, but never exceeds 50% even by the end

[4] https://stats.oecd.org

of the sample period. Of the three months most affected by the lockdowns, the month of April 2020 stands out as the most stressed, as indicated by the proportion of defaults rising to 95.29% in that month. With the exception of the month of July 2020, defaults taper off almost monotonically thereafter through December 2020. In July 2020, the Government of India issued a moratorium on repayment of all loans, hence no defaults are recorded in the dataset. The row labeled 'Moratoriums' shows that 25.79% of borrowers availed themselves of the regulatory relief in July 2020.

Even as borrowers were stressed during, and after the lockdown period, Table 2 shows that they continued to make partial payments on their loans. Partial payments were 89.82% in March 2020, the first month of the lockdown. After falling in May 2020, partial payments started increasing until August 2020, after which more borrowers started paying the monthly amounts due in full. The overpaid and paid-after-due categories rise in numbers in the post-lockdown period from June through December 2020, showing that some of the defaults are being cured either by making up for prior partial payments, or by repayment well after the loan has matured. The lending institution did not assess penalties for late payments due to the unusual circumstance of the pandemic, which helped to encourage borrowers to try and make up any shortfall. Overall, Table 2 shows that as the country was going into lockdown in March 2020, borrowers made an effort to make at least partial payments. But in April and May 2020, when the country was fully in a lockdown, borrowers could no longer hold out and defaulted on their payments. Borrowers in this sector appear to be resilient because soon after lockdowns were lifted, they began to make either full or partial payments, such that defaults had fallen to 5.92% in December 2020 from a peak of 95.29% only eight months earlier.

Table 3 presents the status of loans in terms of the amounts due each month. For instance, the fully paid proportion of 97.51% in November 2019 is the amount due for all loans that satisfy condition (1) of the six conditions above, as a proportion of the sum of the amounts due across all six categories in that month. The trends mirror those in Table 2, showing distress during the lockdown period from April to May 2020, and recovery thereafter. In addition, this table highlights the process by which defaults were cured in the post-lockdown period: In December 2020, 22.76% of loans were paid after maturity. The totals exceed 100% after May 2020 through a combination of paying in excess of the contractual amount in a month, and paying after the loan has matured.

Thus, it appears that borrowers who failed to pay in full during the lockdown, nonetheless, tried to cure defaults through partial payments, paying in excess of contractual requirements, and making payments after the loans had matured.

In the next table, we present the magnitudes of the deficit between the contractual amount due, and the amount collected in that month. Table 4 has the mean, median and mode in INR for the deficit in each month of the sample period, calculated in two ways: i) by individual borrower, and ii) by groups. For the latter, the deficit is calculated as the difference between the contractual amount due and the amount collected in that month aggregated over the members of the group. The table shows that the median and mode for individual borrowers are zero leading up to March 2020. Indeed, the mode deficit is zero even in March 2020, the first Covid lockdown month. In the months of April and May 2020 the mean, median and mode individual deficits are all about INR 2600. Defaults are cured almost immediately thereafter as the mode deficit goes to zero in June 2020 and remains at zero through December 2020. By December 2020, all three statistics are closer in magnitudes to those observed in November 2019, the start of the sample period. Qualitatively similar patterns are evident for group deficits.

Table 4 shows the magnitudes of the deficits shrank rapidly in the post-lockdown period, even though Tables 2 and 3 show that the proportion of fully paid loans in the post-lockdown period never reach the same level as in the pre-lockdown period. We next examine what characteristics explain why some borrowers are unable to repay, particularly during the covid lockdowns. We relate borrowers' ability to repay to macro-economic variables, borrower-specific variables, and loan-specific variables. These variables are: 1) the state in India where the borrower resides, ii) classification of district in which the borrower resides as 'rural', 'semi-urban' or 'urban', iii) educational attainment of borrowers, iv) age of the borrower, v) loan purpose, and vi) size of loan. The state where a borrower resides affects repayment ability if there are exogenous factors, such as political interference into credit markets. The district classification might affect the cohesiveness of a group, with rural groups predicted to be more cohesive, than urban ones (Alibhai, Bessir and Weis (2021)). Borrower-specific variables are drawn from prior literature (Mokhtar, Nartea and Gan (2012)). Educational attainment may be positively related to ability to repay if educational attainment has an independent effect on borrowers' earning capacity. Age of the borrower is a control variable that may be highly correlated with other exogenous characteristics that cannot be measured, such as trustworthiness, and grit. The purpose of the loan is meant to capture the disproportionate effect of covid lockdowns on some economic activities. For instance, economic activities that naturally accommodate social distancing, such as farming, and animal husbandry, were less likely, while retail operations were more likely to be adversely affected by lockdowns. We include loan size as a possible explanatory variable for ability to repay even though the lender offers loans only in three discrete sizes, INR 25,000, INR 26,000 and INR 30,000.

We sort the sample by borrower and loan characteristics and examine the 'compliance' rate, or the proportion of loans in each month with a zero deficit, where deficit is calculated as the difference between the contractual amount demanded by the lender, and the amount collected from the borrower in that month. Results are in Table 5. Panel A examines the proportion of zero deficits by the state in which the borrower resides. We restrict the analysis to states with more than 2% of all borrowers to preclude cases where the inexperience of the lender operating in a particular state affects the ability of their loan officer to make the weekly collections. The table shows that borrowers in the state of Assam consistently had the lowest proportion of re-payers in the post-lockdown period, possibly because local politicians in Assam were exhorting borrowers to default on their microfinance loans. The two states with the lowest number of borrowers, namely, Madhya Pradesh and West Bengal had higher compliance rates than the other two states. Panel B has a sort by district classification. Rates of compliance were similar among the three types of districts in the pre-lockdown period, but from July 2020 onwards, compliance rates were higher in rural districts than in semi-urban or in urban districts.

Panel C of Table 5 has a sort by educational levels of borrowers. We combined missing values for education with those who self-reported as having no formal education. A small majority (50.1%) of the borrowers has some, but fewer than 10 years of schooling. The panel shows that it is the group with no formal schooling that has the highest compliance rate, particularly, in the post-lockdown period starting in June 2020. It appears that this group of borrowers was able to rebound fastest after the lockdowns. Panel D has the sort of borrowers by age. A majority of borrowers (59.5%) were in the 20-40 years age group. There don't appear to be any systematic differences in compliance rates across the three age groups. Panel E has the sort by loan purpose. Borrowers in the agriculture sector had higher compliance rates, both in the pre- and post-lockdown periods.

It is only in the month of March 2020, that borrowers engaged in retail and wholesale trade had higher compliance rates (24.66%). Finally, Panel F shows that, starting in May 2020, there is a monotonic relation between the size of the loan and compliance rates, with larger loans being more likely to be repaid.

5. Regressions

Table 5 shows that there are systematic differences across geography, borrower and loan characteristics that affect compliance rates. These relationships between characteristics and compliance rates do not remain the same during the sample period, but are affected by Covid lockdowns. Earlier, results in Tables 2 and 3 show that even though some borrowers failed to make the contractual monthly payments, they made up the shortfall by paying in excess of the contractual payments in subsequent months, or by making payments well after the loans had matured. We next determine whether the Covid lockdowns had a permanent effect on the ability of borrowers to repay by estimating panel regressions. The panel regressions will also help us identify the characteristics of borrowers for whom Covid lockdowns permanently affected their ability to repay. We identify all loans that had matured on or before December 2020. There were 35,820 loans out of the original sample of 54,763 loans that met the criterion. From these, we create two sub-samples: i) loans that were fully paid off, and ii) loans that were not fully repaid by December 2020. 43.32% (15,518 borrowers) belong to the first sub-sample, while the remaining 56.68% belong to the second sub-sample.

We pool all borrowers by month in that sub-sample into a panel. We estimate panel regressions with the fourteen months in the sample period as explanatory variables, in addition to borrower-specific, and loan-specific control variables. The dependent variable in the regressions is the monthly deficit, or the difference in INR between the contractual monthly payment, and the monthly collection. We include state fixed effects to account for the evidence in the previous table that borrowers in the state of Assam were pressured by politicians to default on their microfinance loans. The borrower specific variables are i)'education' that takes a value 1(0) if the borrower had no (some) formal schooling, ii) 'purpose' that takes a value 1 if the purpose of the loan was for agriculture, animal husbandry, or, to buy farming equipment, and takes a value 0 for all other purposes, and, iii) the age of the borrower. There are two loan-specific variables that are included as explanatory variables, i) the vintage of the loan in that month, and ii) the loan amount scaled by household income. Finally, we include an independent variable to capture the effect of the group lending model. The net group deficit calculated as the group deficit aggregated across all five borrowers in a group net of the borrower's deficit in that month.

If the group lending model captures the risk of default, the net group deficit should subsume the explanatory power of all other independent variables. Any marginal explanatory power retained by an independent variable in the presence of group deficit suggests that the group lending model does not insulate the MF portfolio from idiosyncratic default risk. In particular, statistically significant coefficients on the Covid lockdown months would indicate that members in a group were not equally affected by Covid lockdowns.

Results are presented in Panels A and B of Table 6. The first specification (i) includes only the fourteen months in the sample period as fixed effects. Loan-specific and borrower-specific variables are added in specification (ii), and the net group deficit is added in specification (iii). Results presented in Panel A of Table 6 show that in the sample of borrowers who fully paid off their loans by December 2020, the effect of Covid lockdowns was temporary: only the coefficients on months March through August 2020 are positive and statistically significant in the first specification. The magnitudes of the coefficients capture the amounts of the deficit in those months. The coefficients on March through July 2020 remain statistically significant in the second specification, while the coefficient on the month of August 2020 is no longer significant, being subsumed by the other explanatory variables. Finally, in specification (iii) only the coefficients on April and May 2020 remain positive and statistically significant when net group deficit is also included as an independent variable. The coefficients on all other months turn negative, indicating payments in excess of contractual amounts; default due to Covid lockdowns was reversed in subsequent months through over-payments. Among other independent variables, the coefficients on net group deficit, vintage, and scaled loan are all positive and significant. Thus, the results show that Covid lockdowns had an idiosyncratic, albeit temporary, effect on default risk only in the months of April and May 2020.

Results in Panel B of Table 6 show that in the sub-sample of borrowers who did not fully repay their loans by the end of December 2020, the coefficients on all months are positive and statistically significant in the first specification. A comparison of the coefficients show that they are substantially higher than the corresponding coefficients for the sub-sample that repaid their loans. In the second specification, the coefficients on March 2020 through December 2020 remain positive and statistically significant even in the presence of loan, and borrower-specific variables. The magnitudes of the coefficients are roughly 15-20% of those in the first specification, which are to be interpreted as the incremental magnitudes of default that cannot be explained by systematic factors. The coefficients on March through December 2020 remain positive and continue to be statistically significant in the third specification even in the presence of net group deficit. These results show that Covid lockdowns had a permanent effect on default risk in the portfolio. The default risk is idiosyncratic in that default cannot be fully explained by the group lending model. These borrowers may be identified from the coefficients on the borrower-specific variables: the negative coefficients on education and age indicate they are likely to be younger residents with some education.

Group lending appears to be largely successful in reducing idiosyncratic risk of borrower default. In other words, the effect of an exogenous shock like Covid lockdowns is mitigated by the behavior of the group: borrowers follow the lead of other members in the group in most months, except during the lockdown months. We set out to identify whether group default can be predicted by characteristics of the group. Results from such an analysis will inform lenders about the factors they will need to consider in forming groups.

We calculate the group outstanding balance at the end of Dec 2020, for all loans that matured on or before that date. A logistic regression is estimated with a dummy variable that takes a value of 1(0) if the outstanding balance is not equal (equal) to zero. The explanatory variables are the mean loan amount among all borrowers in that group, total household income, total loan amount scaled by total household income. In addition, we include the three qualitative independent variables described earlier, namely, district classification of borrower's residence, purpose of the loan and educational attainment. For the group, we assigned the qualitative variable that had a frequency greater than 60% among individuals in that group. In other words, the qualitative variable assigned to a group is that which applied to at least three of the five borrowers in that group. State fixed effects are included in the regression.

Results from the group logistic regression are reported in Table 7. The positive and statistically significant coefficient on mean loan amount indicates higher loan amounts are associated with a higher risk of default. Considering that the lender only had three loan sizes, 25,000, 26,000 and 30,000 INR, the negative impact of loan size on default risk is economically significant. The coefficient on total household income is positive and statistically significant, which is an anomaly that we cannot readily explain with any economic theory. Perhaps the group lending model is less persuasive among relatively affluent borrowers. The same explanation likely applies to groups that are based in urban districts, the coefficient on which is positive and statistically significant; urban groups are less sensitive to peer pressure, perhaps because there is greater anonymity afforded in an urban setting. Groups whose members are primarily engaged in trading are less likely to default, while those engaged in farming are more likely to default. Scaled loan amount has no incremental explanatory power. None of the educational attainment variables have incremental explanatory power.

6. Contagion of default

Contagion is the phenomenon where default by one borrower has an impact on otherwise healthy borrowers (Helwege and Zhang (2016)). The exogenous source of contagion in this study are the Covid lockdowns. The group lending model relies on social capital and social inclusion to ensure prompt repayments to lenders. Contagion is predicted to be low when the value of social capital is high so that borrowers fear social exclusion upon failure to repay the lender. Contagion may be high however when borrowers are faced with an exogenous shock. In that scenario, borrowers might be excused by their social peers for failure to repay when neighboring groups are defaulting on their loans.

We rely on proximity to defaulting neighbors to test for contagion. We focus on village level defaults as the source of contagion. Montgomery (1996) shows that it is the larger village-level group rather than a particular five-member group that is key to ensuring repayment discipline. They find that peer-pressure applied at the level of the village administration is stronger, indeed coercive in some instances, than peer-pressure from the other four members in a group. In each month in the sample, we calculate monthly deficit by village, and identify villages with the largest deficit. We measure the strength of contagion, if any, by geographic proximity of borrowers to the distressed village. Our choice of geographic proximity is based on evidence in Karlan (2007) who finds lower rates of default among members who are in close geographic proximity to each other, and who share cultural similarity. In other words, social capital is higher among culturally similar borrowers who live close to each other.

For each month in the sample, we identify the village(s) with the largest magnitude of deficit, which was earlier defined as the difference in INR between the contractual monthly payment, and the monthly collection. We label these villages as 'distressed villages' in the sample. There were a total of 35 'distressed' villages, zero in the state of Tripura, one each in the states of Chattisgarh and Madhya Pradesh, four in the state of Assam, 15 in the state of Odisha, and 14 in the state of West Bengal. We rely on Google Maps to calculate the distance from each of these 'distressed' villages to the headquarters of every district in that state. We identify district headquarters from websites maintained by the State governments of Assam, Odisha, Tripura, West Bengal, Chattisgarh, and Madhya Pradesh. Every borrower group in a particular state and district is ranked based on the distance from the district headquarters to the distressed village(s). When there are multiple villages in a district that are 'distressed', we select the village closest to the district headquarters to determine the ranking. For borrower groups in districts that had no distressed villages, the distance is set to zero.

Earlier tables (Tables 2 and 3) showed that the highest proportion of defaults occurred in April 2020. We therefore label April 2020 as month zero and trace defaults by groups from month zero through to December 2020, the last month in the sample. Two states, West Bengal and Odisha, accounted for all distressed villages in April 2020. Borrower groups in these two states are divided into three categories: i) those from districts in the states with no distressed village, ii) those from districts closest to the distressed village, and, iii) those from districts furthest to the distressed village.

The mean deficit, or the difference between the amount due to the lender and the amount collected by the lender is calculated for each borrower group in each category for every month following month zero. Mean deficits for each of the three groups are plotted in Figure 2 for borrower groups from these two states. In the plot for West Bengal, the no-default category has the highest amount outstanding, followed by the category with the longest distance to the distressed village. The category of borrower groups that has the shortest distance to the distressed villages has the lowest amount outstanding by December 2020, indicating a lack of default contagion from the distressed village to neighboring villages. The plot for Odisha is qualitatively similar though the relation between the amount outstanding and distance to distressed villages changes over the months following month zero. The borrower groups in districts with no distressed villages has the lowest amount outstanding in month zero. It reverses starting in month 1, when borrower groups in districts with the shortest distance to a distressed village have the lowest amount outstanding by December 2020. Thus, there is no evidence in Figure 2 that borrower groups in close proximity to distressed villages suffered from contagion. On the contrary, there is stronger evidence that the threat of diminishing social capital for defaulting was effective in forcing borrowers living in close proximity to the distressed village, to repay their loans.

7. Conclusions

Our study adds to a large literature on default in the microfinance sector. Our contribution is twofold: First, we document that the Covid pandemic had a temporary impact on defaults in that defaults had fallen to 5.92% in December 2020 from a peak of 95.29% only eight months earlier during the height of the Covid pandemic in April 2020. Our results show that MF is a sustainable business even under an exogenous shock. Second, we demonstrate that social capital that is the foundation of the Group Lending model is successful in preventing default contagion. Geographic proximity, our proxy for social capital, to distressed villages increases peer-pressure among borrowers in neighboring villages to repay. The limitation of the study is that it is confined to a single microfinance institution in India. Nonetheless our results add to our understanding of the risk-return profile of the MF sector, which to date, accounts for over $115 billion in lending worldwide, and for over $25 billion in India alone[5].

[5] "Vision of microfinance in India", November 2019, SIDBI-PwC Joint report, and "India: Microfinance and Financial Sector Diagnostic Study, June 2008, IFC-kfw joint report.

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Table 1
Univariate Statistics

Panel A

	# of obs	*mean*	*median*	*std.dev*	*Quartile 1*	*Quartile 3*
Borrower Age (in years)	54762	37.9	37.55	9.45	30.2	44.9
Loan amount (in INR)	54763	26535	25000	3793	25000	30000
Household income (in INR)	54606	8401	9000	2122	8000	10000
Family size	16292	4.10	4.00	1.23	3	5
Interest rate (%)	54763	24.23	24.5	0.65	23.50	24.50

Panel B

State	*% of all borrowers*
Odisha	53.32
Assam	18.38
Chattisgarh	11.41
Madhya Pradesh	11.17
West Bengal	5.52
Tripura	0.2

Panel C

Education	*% of all borrowers*
Not reported	12.15
No schooling	16.56
9th pass	32.19
10th fail	11.58
10th pass	12.65
Diploma holder	0.03
Under-graduate	0.66
Graduation	0.81
Post graduation	0.37
Professionally qualified	0.10
Agricultural management	1.13
Doctorate	0.01
Non-traditional schooling	11.77

Table 1 (continued)

Panel D

Purpose of loan	***% of all borrowers***
Agriculture Equipment	7.19
Agriculture-Fruit &	2.47
Agriculture-Live	17.31
Agriculture–Allied	4.42
Agriculture–Farming	28.27
Others–Agriculture	25.97
Services-Auto/equipment	0.57
Services-Fast food/food	0.62
Services-Other	4.22
Trading-Cloth/Fabric	0.54
Trading-Grocery/General	1.3
Trading-	0.32
Trading-Other	6.79

Panel E

Classification of district of borrower's residence	***% of all borrowers***
Rural	91.6
Semi-Urban	6.55
Urban	1.85

Table 2
Status of loans (number) by month

'Active' refers to loans for which collections are due. 'fully paid' is the loans that fully paid what was owed. 'partial paid' is the loans that partially paid what was owed. 'moratorium' is the loans for which payment has been waived. 'default' is the loans that did not pay any of what was owed, or collection was not waived. The numbers in the table are the loans in each category as a percent of active loans. Each loan is to a person. Defaults are 0% in July because of a moratorium imposed by the Government of India.

			2020											
Status	**Nov 2019**	**Dec 2019**	**Jan**	**Feb**	**March**	**April**	**May**	**June**	**July**	**August**	**Sept.**	**Oct.**	**Nov.**	**Dec.**
Active loans	32,338	35,820	39,014	42,596	47,841	46,896	46,979	47,147	46,315	45,551	46,777	46,217	43,809	41,115
fully paid (%)	97.51	95.24	95.01	95.18	5.85	0.05	2.06	22.99	24.83	25.36	36.34	38.90	41.21	37.56
Default (%)	0.61	0.61	1.03	1.38	3.36	95.29	61.60	25.68	0.00	19.38	10.30	9.65	7.46	5.92
Moratorium (%)	0.07	0.12	0.13	0.24	0.37	1.94	4.16	0.34	25.79	0.79	1.05	1.76	1.92	1.72
partial paid (%)	0.90	3.48	2.13	2.36	89.82	2.65	30.65	47.75	44.10	46.72	38.94	31.89	25.06	19.90
Overpaid (%)	0.90	0.55	1.71	0.83	0.56	0.07	1.00	3.19	4.70	5.37	5.72	5.79	5.43	6.63
Paid after due (%)	0.00	0.00	0.00	0.01	0.04	0.00	0.53	0.05	0.58	2.38	7.65	12.01	18.92	28.28

Table 3

Status of loans by amount due by month

Numbers exceed 100% because of over-payment, and fall below 100% because invoices didn't start on a timely basis.

	Nov 2019	***Dec 2019***	***Jan 2020***	***Feb 2020***	***March 2020***	***April 2020***	***May 2020***	***June 2020***	***July 2020***	***August 2020***	***Sept. 2020***	***Oct. 2020***	***Nov. 2020***	***Dec 2020***
Total due (INR in '000s)	74,834	88,963	100,354	94,054	115,999	119,542	111,491	120,017	93,145	106,385	117,194	112,719	101,182	102,898
Fully paid (%)	97.51	95.13	94.80	95.14	4.37	0.05	2.20	23.01	34.35	26.39	37.04	40.30	43.91	41.69
Default (%)	0.59	0.61	1.01	1.45	2.21	96.02	63.39	25.16	0.00	19.63	10.72	10.22	7.98	6.48
Moratorium (%)	0.02	0.39	0.08	0.13	0.00	0.00	0.39	0.07	0.12	0.48	0.02	0.42	0.01	0.07
Partial paid (%)	0.97	3.74	2.36	2.62	92.84	2.86	32.55	48.52	60.23	49.31	41.25	34.82	27.21	22.46
Overpaid (%)	1.26	0.82	2.67	2.15	0.95	0.09	1.59	4.69	8.41	8.11	9.59	9.92	9.51	11.20
Paid after due (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.90	9.51	15.60	22.76
Total (%)	100.36	100.68	100.91	101.48	100.37	99.01	100.12	101.45	103.11	103.93	104.52	105.20	104.22	104.65

Table 4
Difference between amount demanded and amount collected for individual borrowers and groups

For all active loans, the difference ('deficit') between the amount demanded by the lender and the amount collected is calculated. Group statistics are calculated based on group affiliation of individual borrowers. Individual borrowers are assigned to groups, with each group consisting of five borrowers, usually drawn from the same pool of friends and family.

	Individual borrowers' Amount demanded- amount collected			*Borrower Group's Amount demanded- amount collected*		
Month	Mean (in INR)	Median (in INR)	Mode (in INR)	Mean (in INR)	Median (in INR)	Mode (in INR)
Nov 2019	-0.001	0	0	0.16	0	0
Dec 2019	0.232	0	0	1.33	0	0
Jan 2020	26.325	0	0	122.78	0	0
Feb 2020	24.328	0	0	111.57	0	0
March 2020	721.577	900	0	3,852.22	5,160	0
April 2020	2,549.290	2,680	2,700	12,488.00	12,520	13,500
May 2020	2,258.830	2,260	3,375	11,785.93	12,160	14,125
June 2020	1,214.210	1,175	0	5,963.08	5,600	0
July 2020	1,213.040	1,350	0	6,369.29	6,730	0
August 2020	966.462	900	0	4,578.68	4,280	0
Sept. 2020	812.125	675	0	4,478.42	4,580	0
Oct. 2020	622.060	65	0	2,797.23	1,820	0
Nov. 2020	901.525	680	0	5,559.09	5,630	0
Dec 2020	2.643	0	0	18.93	6	0

Table 5
Borrower characteristics and ability to repay

The percent of loans each month with a zero deficit, where deficit = monthly amount demanded-monthly amount collected.

Panel A: By state

State	*% of borrowers*	*Nov 2019*	*Dec 2019*	*Jan 2020*	*Feb 2020*	*Mar 2020*	*April 2020*	*May 2020*	*June 2020*	*July 2020*	*August 2020*	*Sept. 2020*	*Oct. 2020*	*Nov. 2020*	*Dec. 2020*
Orissa	59.72%	97.51%	96.57%	96.14%	96.71%	7.40%	0.00%	1.00%	19.47%	28.17%	22.46%	41.10%	45.00%	49.96%	49.27%
WBengal	7.17%	99.87%	99.70%	99.73%	99.68%	0.50%	0.26%	6.63%	31.92%	41.17%	28.58%	43.27%	48.89%	57.01%	59.77%
Madhya	8.68%	99.91%	97.38%	98.24%	99.74%	4.20%	0.01%	0.92%	33.32%	57.82%	48.64%	59.11%	58.80%	55.44%	48.43%
Assam	24.44%	97.58%	87.07%	85.53%	83.05%	1.12%	0.00%	1.23%	14.39%	13.08%	12.45%	15.08%	10.60%	7.12%	3.53%

Panel B: By type of district

		Nov 2019	*Dec 2019*	*Jan 2020*	*Feb 2020*	*Mar 2020*	*April 2020*	*May 2020*	*June 2020*	*July 2020*	*August 2020*	*Sept. 2020*	*Oct. 2020*	*Nov. 2020*	*Dec. 2020*
Rural	91.81%	97.48%	95.20%	94.73%	94.92%	4.71%	0.05%	2.12%	23.54%	34.74%	26.77%	37.85%	40.98%	44.74%	42.69%
Semi-urban	5.17%	96.95%	94.49%	95.48%	97.57%	1.34%	0.00%	2.71%	15.61%	31.57%	23.17%	29.16%	34.32%	36.50%	31.72%
Urban	2.02%	99.19%	93.80%	95.53%	96.34%	1.16%	0.00%	4.25%	27.15%	28.19%	21.59%	29.98%	33.82%	35.42%	36.27%

Panel C: By education

		Nov 2019	*Dec 2019*	*Jan 2020*	*Feb 2020*	*Mar 2020*	*April 2020*	*May 2020*	*June 2020*	*July 2020*	*August 2020*	*Sept. 2020*	*Oct. 2020*	*Nov. 2020*	*Dec. 2020*
Zero school	31.08%	97.26%	94.42%	94.43%	95.38%	5.47%	0.06%	2.49%	24.76%	38.71%	29.02%	37.61%	44.45%	48.39%	46.06%
<10 years	50.14%	97.54%	95.77%	95.12%	95.49%	4.16%	0.06%	1.90%	21.94%	33.06%	24.87%	35.79%	36.73%	40.14%	37.69%
>10 years	18.78%	96.85%	93.12%	92.85%	92.44%	3.18%	0.04%	3.19%	23.86%	33.29%	25.84%	34.75%	39.84%	44.60%	43.03%

Table 5 (continued)

Panel D: By age

		Nov 2019	*Dec 2019*	*Jan 2020*	*Feb 2020*	*Mar 2020*	*April 2020*	*May 2020*	*June 2020*	*July 2020*	*August 2020*	*Sept. 2020*	*Oct. 2020*	*Nov. 2020*	*Dec. 2020*
20-40	59.50%	97.40%	95.13%	94.80%	95.12%	4.11%	0.06%	2.30%	22.98%	34.16%	26.07%	36.37%	39.80%	43.44%	40.71%
40-50	28.62%	97.76%	95.23%	94.91%	95.30%	4.92%	0.03%	2.20%	23.28%	35.36%	27.24%	38.38%	41.71%	45.14%	43.54%
50-100	11.87%	97.26%	94.86%	94.57%	94.89%	4.41%	0.05%	1.86%	22.60%	33.10%	26.08%	37.37%	39.95%	43.86%	42.83%

Panel E: By loan purpose

		Nov 2019	*Dec 2019*	*Jan 2020*	*Feb 2020*	*Mar 2020*	*April 2020*	*May 2020*	*June 2020*	*July 2020*	*August 2020*	*Sept. 2020*	*Oct. 2020*	*Nov. 2020*	*Dec. 2020*
Agriculture	67.33%	97.55%	95.31%	94.71%	95.77%	3.27%	0.05%	2.38%	24.33%	35.17%	27.21%	38.39%	41.54%	45.99%	44.17%
Animal husbandry	17.18%	98.27%	94.74%	95.48%	94.12%	5.47%	0.01%	1.86%	20.57%	33.18%	24.77%	32.87%	36.76%	37.87%	33.51%
Services	5.65%	98.12%	96.78%	96.36%	95.28%	2.25%	0.13%	1.35%	15.80%	29.60%	22.21%	36.66%	37.42%	35.35%	33.25%
Trade	9.84%	95.30%	93.44%	93.01%	90.68%	24.66%	0.02%	1.31%	14.65%	21.32%	17.91%	23.58%	29.41%	28.41%	26.16%

Panel F: By size of loan

		Nov 2019	*Dec 2019*	*Jan 2020*	*Feb 2020*	*Mar 2020*	*April 2020*	*May 2020*	*June 2020*	*July 2020*	*August 2020*	*Sept. 2020*	*Oct. 2020*	*Nov. 2020*	*Dec. 2020*
25K	23.19%	97.65%	96.71%	96.64%	94.62%	6.38%	0.11%	1.96%	18.95%	18.50%	19.19%	28.34%	27.10%	26.61%	19.47%
26K	41.19%	97.60%	95.59%	95.38%	94.73%	7.76%	0.01%	1.11%	19.38%	21.31%	21.16%	33.01%	31.64%	29.03%	22.44%
30K	35.62%	97.32%	93.98%	93.56%	93.23%	3.40%	0.06%	2.79%	25.63%	27.32%	26.81%	34.52%	36.05%	37.40%	33.26%

Table 6
Panel Regressions with individual borrowers whose loans matured at end of Dec 2020

Two sets of regressions are estimated; a set each with borrowers whose loans matured in Dec 2020, and who had zero outstanding balance, and a second set of borrowers who had an outstanding balance in Dec 2020. Panel regressions are estimated by pooling individual borrowers across months. Fixed effects for state are included in the regressions. Dependent variable is the monthly deficit, which is the difference between amount demanded and amount collected. The borrower specific variables are: 1) 'education' that takes a value 1(0) if the borrower had no (some) formal schooling, 2) 'purpose' that takes a value 1if the purpose of the loan was for agriculture, animal husbandry, to buy farming equipment, and takes a value 0 for all other purposes, 3) 'village' that takes a value 1(0) if the borrower lives in a district classified as being rural (semi-urban or urban), and, 4) the age of the borrower. The loan-specific variables are: 1) the vintage of the loan in that month, and 2) the loan amount scaled by household income.

Panel A: Sub-sample of borrowers who fully repaid their loans by Dec 2020

	(i)		(ii)		(iii)	
Observations	176,180		166,676		32,198	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Nov 2019	-4.23	-0.48	-86.21***	-5.33	-79.87**	-2.49
Dec 2019	2.76	0.32	-97.24***	-5.89	-99.53***	-3.03
Jan 2020	-14.77*	-1.70	-135.58***	-7.96	-158.60***	-4.68
Feb 2020	-67.98***	-7.73	-206.47***	-11.70	-211.11***	-6.00
March 2020	512.66***	56.94	389.06***	21.18	0.25	0.01
April 2020	2417.50***	254.47	2255.57***	117.66	681.87***	16.10
May 2020	1655.49***	171.88	1495.40***	74.73	356.19***	8.47
June 2020	661.01***	70.16	455.79***	21.76	-113.57***	-2.69
July 2020	321.30***	33.16	97.22***	4.44	-247.48***	-5.66
August 2020	235.02***	22.45	-1.49	-0.07	-357.45***	-7.84
Sept. 2020	-81.02***	-7.73	-340.29***	-14.18	-502.45***	-10.49
Oct. 2020	-289.19***	-23.55	-557.77***	-21.94	-671.30***	-13.23
Nov. 2020	-610.11***	-43.53	-896.23***	-32.85	- 1006.78***	-18.45
Dec 2020	-273.57***	-31.58	-636.24***	-22.98	-647.87***	-11.73
Vintage of loan			19.19***	13.15	24.23***	8.37
Scaled loan			5.73***	3.43	6.22**	2.05
District type			-6.92	-1.24	-4.01	-0.35
Education			9.26*	1.66	-6.85	-0.61
Loan purpose			0.02	0.08	-0.18	-0.30
Deficit for group					0.15***	82.90
Adj R-sq (%)	33.51		33.83		45.74	

Table 6 (continued)

Panel B: Sub-sample of borrowers who did not repay in full by Dec 2020

	(i)		(ii)		(iii)	
Observations	277,076		275,690		52,695	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Nov 2019	27.65***	4.42	-73.19***	-7.44	-0.78	-0.04
Dec 2019	64.08***	11.11	-68.07***	-7.06	-7.99	-0.43
Jan 2020	62.36***	10.82	-118.57***	-11.99	-34.06*	-1.77
Feb 2020	102.31***	17.74	-125.97***	-12.32	-36.62**	-1.85
March 2020	738.85***	128.07	476.40***	44.81	213.64***	10.31
April 2020	2559.52***	439.99	2249.82***	202.48	984.64***	42.01
May 2020	2291.33***	391.78	1936.47***	166.42	853.64***	35.75
June 2020	1707.78***	295.80	1307.69***	107.00	606.62***	25.06
July 2020	668.43***	115.06	218.47***	17.02	68.17***	2.74
August 2020	1471.35***	249.83	979.28***	72.78	464.60***	17.67
Sept. 2020	1221.62***	210.86	679.82***	47.88	316.43***	11.47
Oct. 2020	1200.63***	204.94	611.85***	41.08	307.26***	10.64
Nov. 2020	1006.89***	169.73	375.00***	24.03	187.50***	6.21
Dec 2020	872.59***	151.33	193.69***	11.77	82.84***	2.60
Vintage of loan			47.09***	49.58	31.99***	17.35
Scaled loan			24.17***	21.25	17.60***	7.75
District type			-76.56***	-23.48	-45.17***	-7.10
Education			48.25***	14.83	6.61	1.04
Loan purpose			-1.77***	-10.76	-2.24***	-6.97
Deficit for group					0.13***	138.08
Adj R-sq (%)	47.59		48.74		62.37	

Notes: *, **, and ***denotes significance at the 10%, 5%, and 1% level, respectively.

Table 7
Logistic Regressions for group likelihood of default.

All individual borrowers are assigned to groups. We calculate the group outstanding balance at the end of Dec 2020 for groups whose loans have matured by Dec 2020. If the outstanding balance is not zero, a dummy variable ‘pass’ is set to 1 and 0 if the loan balance is zero. A logistic regression is estimated in Dec 2020 for ‘pass’ with explanatory variables.

observations	*6,576*	*T_stats*
Intercept	-2.425***	-6.27
Mean loan amount for group	0.0001***	9.28
Total household income	0.00002***	3.24
Total loan amount/total household income	0.001	0.02
Purpose=trading	-1.190***	-12.72
Purpose=service	0.197**	1.96
Purpose=farming	0.484***	8.93
Education= some schooling	0.332	1.51
Education= no schooling	0.087	0.40
Education=college educated	0.011	0.04
Type of district=urban	0.404***	5.80
Adj R-square (%)	10.28%	

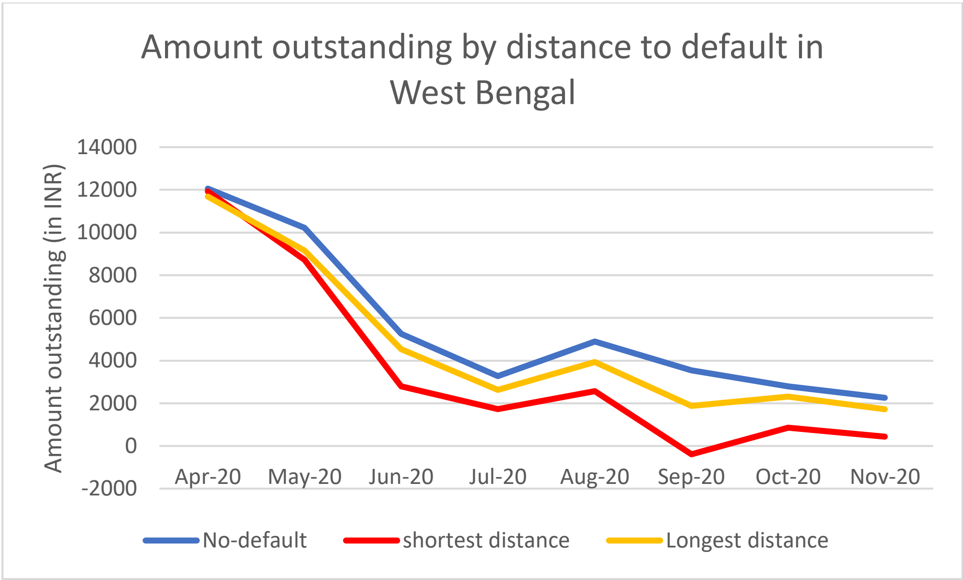
Notes: *, **, and ***denotes significance at the 10%, 5%, and 1% level, respectively.

Figure 2

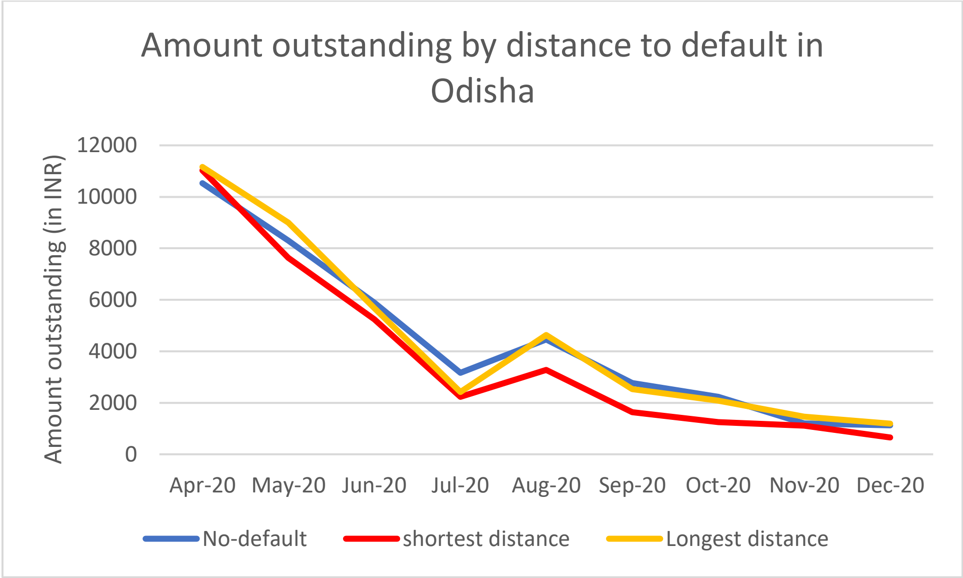
Contagion of default

Villages with the largest deficit aggregated over all groups in that village are identified for April 2020. Villages in the state are sorted into three groups based on their proximity to the capital of the district with the most distressed village.

Panel A: Borrowers in West Bengal



Panel B: Borrowers in Odisha



Appendix A.1

List of variables in dataset

Branch	*nov2019_collection*
Center	nov2019_demand
closing data	dec2019_collection
customer number	dec2019_demand
cycle	jan2020_collection
date of birth_borrower	jan2020_demand
date of birth_co borrower	feb2020_collection
date of first installment	feb2020_demand
date of last installment	mar2020_collection
distribution date	mar2020_demand
District	apr2020_collection
Education	apr2020_demand
Education_co borrower	may2020_collection
Family dependents	may2020_demand
Family size	jun2020_collection
Frequency	jun2020_demand
Group	jul2020_collection
Household income	jul2020_demand
Installment	aug2020_collection
interest	aug2020_demand
Loan amount	sep2020_collection
Religion	sep2020_demand
Tenure	oct2020_collection
	oct2020_demand
	nov2020_collection
	nov2020_demand
	dec2020_collection
	dec2020_demand

Appendix A.2
Month by month Regressions with firms which defaulted +1(0) in Dec 2020

	Nov-19	Dec-19	Jan-20	Feb-20	Mar-20	Apr-20	May-20	Jun-20	Jul-20	Aug-20	Sep-20	Oct-20	Nov-20	Dec-20
	20117	20117	20117	20117	20117	20117	20117	20117	20117	20117	20117	20117	20117	20117
Intercept	-0.879	-3.244	-3.487	-4.156	7.058	23.293	8.349	-1.212	-3.845	-4.468	-3.717	-5.842	-8.816	-13.365
	(-10.68)	(-24.66)	(-25.43)	(-27.40)	(23.71)	(20.41)	(10.60)	(-6.80)	(-21.29)	(-24.34)	(-28.82)	(-42.31)	(-59.14)	(-64.72)
urban	0.119	0.152	0.003	-0.243	0.883	3.311	-0.808	0.432	0.230	0.126	0.294	0.156	0.147	0.163
	(14.94)	(8.23)	(0.10)	(-5.32)	(5.89)	(6.59)	(-4.89)	(8.93)	(7.15)	(3.80)	(11.49)	(6.41)	(5.66)	(5.53)
trading	0.203	0.230	0.125	0.171	10.556	1.237	9.449	0.265	0.592	0.369	-0.005	-0.216	-0.287	-0.446
	(1.61)	(2.12)	(1.19)	(1.61)	(123.53)	(6.93)	(52.31)	(1.43)	(2.77)	(2.02)	(-0.05)	(-2.31)	(-2.91)	(-3.62)
services	-0.214	-0.508	-0.434	-0.327	-0.861	1.292	-1.899	0.351	0.239	0.066	-0.242	-0.214	-0.110	-0.042
	(-2.41)	(-4.36)	(-4.19)	(-3.56)	(-2.27)	(7.42)	(-3.07)	(3.04)	(2.04)	(0.63)	(-3.77)	(-3.23)	(-1.58)	(-0.43)
farming	0.086	-0.051	0.096	0.016	-1.678	-7.142	-2.008	-0.159	-0.215	-0.137	0.038	0.134	0.135	0.188
	(2.98)	(-1.48)	(2.91)	(0.44)	(-16.32)	(-8.56)	(-8.58)	(-3.22)	(-3.87)	(-2.70)	(1.19)	(4.21)	(4.10)	(4.69)
equip	0.015	0.511	0.525	0.428	-2.232	1.495	-2.597	-0.473	-0.158	-0.093	0.356	0.237	0.080	0.149
	(0.40)	(11.87)	(10.53)	(6.93)	(-14.25)	(8.76)	(-8.39)	(-7.13)	(-2.04)	(-1.23)	(6.19)	(4.21)	(1.47)	(2.19)
animal	0.033	0.041	-0.138	0.199	-3.401	1.410	-1.375	0.131	0.095	0.179	0.163	0.255	0.372	0.406
	(1.18)	(1.12)	(-3.22)	(4.76)	(-42.05)	(8.30)	(-3.42)	(2.12)	(1.46)	(2.93)	(4.14)	(6.54)	(9.05)	(7.97)
none	-0.149	-0.307	-0.243	-0.628	0.370	1.738	-2.524	-0.081	-0.226	-0.167	0.059	-0.039	-0.105	-0.118
	(-5.80)	(-4.49)	(-3.86)	(-8.30)	(5.47)	(8.63)	(-10.22)	(-1.92)	(-5.61)	(-4.17)	(1.72)	(-1.11)	(-2.92)	(-2.85)
middle	0.006	-0.211	-0.193	-0.096	-0.097	2.108	-2.633	0.178	0.130	0.118	0.098	0.150	0.146	0.042
	(0.23)	(-3.77)	(-3.65)	(-1.69)	(-1.49)	(10.42)	(-12.49)	(4.56)	(3.51)	(3.23)	(3.33)	(4.91)	(4.56)	(1.12)
high	0.128	0.438	0.454	0.706	-0.007	-7.435	-2.034	0.274	0.506	0.467	0.279	0.338	0.269	0.277
	(4.57)	(8.34)	(8.96)	(13.02)	(-0.09)	(-9.28)	(-7.31)	(5.96)	(11.07)	(10.25)	(8.30)	(9.83)	(7.65)	(6.54)
college	0.012	-0.055	-0.056	-0.177	-0.026	1.443	9.213	-0.362	-0.559	-0.614	-0.446	-0.466	-0.344	-0.190
	(0.26)	(-0.36)	(-0.39)	(-1.10)	(-0.22)	(7.00)	(60.98)	(-5.31)	(-7.52)	(-8.65)	(-7.03)	(-6.93)	(-4.85)	(-2.47)
age	0.001	0.002	0.000	-0.003	-0.008	0.036	0.014	-0.003	0.004	-0.002	-0.004	-0.005	-0.002	-0.004
	(0.53)	(0.57)	(0.15)	(-0.93)	(-1.71)	(12.40)	(1.02)	(-1.17)	(1.52)	(-0.99)	(-1.89)	(-2.81)	(-1.20)	(-1.86)
scaloan	0.013	-0.023	-0.032	-0.032	0.045	-0.097	0.044	0.090	0.106	0.105	0.016	-0.024	-0.023	0.006
	(1.75)	(-2.33)	(-1.56)	(-1.27)	(0.84)	(-4.54)	(0.57)	(3.32)	(4.11)	(4.02)	(1.17)	(-1.86)	(-1.89)	(0.36)
Loan-age	-1.813	0.251	0.258	0.321	0.038	0.184	0.103	0.478	0.663	0.659	0.481	0.618	0.798	1.134
	(-74.34)	(33.07)	(33.14)	(36.71)	(3.11)	(10.78)	(1.46)	(33.17)	(46.27)	(47.14)	(52.45)	(67.33)	(84.45)	(86.31)
Adj R-sq	53.89	5.19	5.34	10.32	7.29	23.69	5.1	10.4	18.22	17.46	14.01	19.48	26.59	33.63