Community Influence on Microfinance Loan Defaults under Crisis Conditions: Evidence from Indian Demonetization

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The microfinance “group lending” approach has achieved widespread success in promoting high rates of repayment, and thus the viability of financial access, in very low-income environments. Yet group lending, which relies on social connections between borrowers to reinforce repayment, may be vulnerable under crisis conditions in which defaults are commonplace. We explore this possibility in the context of the liquidity crisis that followed India’s 2016 demonetization policy. Using proprietary data on the repayment behavior of about two million microfinance borrowers, we find evidence of disproportionate localization of defaults within lending communities. Further analysis reveals evidence consistent with borrower-to-borrower spread of defaults not only through formal joint-liability connections but also through informal community-level connections, the latter effect being especially pronounced for borrowers from the same religion.

Keywords: Microfinance; Group Lending; Loan Defaults; Communities; Demonetization

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1. INTRODUCTION
A growing literature in strategic management highlights the importance of microfinance as a vehicle for financial inclusion in emerging markets (Ault & Spicer, 2014; Battilana & Dorado, 2010; Bruton, Khavul, & Chavez, 2011; Cobb, Wry, & Zhao, 2016; Wry & Zhao, 2018). A distinctive feature of microfinance is its widespread reliance on the “group lending” approach, which conducts lending operations at the level of the community in order to serve a large number of low-income borrowers at relatively low cost. Through group lending, microfinance organizations originate tens of millions of new loans every year, thus significantly expanding access to finance around the world (Banerjee, 2013; Canales & Greenberg, 2016). Many of these loans occur in impoverished settings where alternative, conventional lending practices, such as the holding of collateral, are impracticable (Canales, 2014; Singh, Dutt, & Adbi, 2022).1

The essential feature of the group lending approach is its reliance on social connections among borrowers to normalize and enforce timely loan repayment (Haldar & Stiglitz, 2016). Loan administration is conducted in lending centers, each composed of multiple joint-liability groups, which bring borrowers into regular contact with other borrowers. Some of these social connections are formalized as joint-liability contracts that make borrowers responsible not only for timely repayment of their own loans, but also for those held by a group of their peers, thus creating a system of “social collateral” characterized by borrowers’ accountability not only to the lender, but also to each other (Besley & Coate, 1995; Ghatak & Guinnane 1999). Through participation in frequent, mandatory meetings organized by the microfinance organization for borrowers living in the same community, borrowers also build informal, non-economic social

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1 The global microfinance industry originated approximately $157 billion in loans in 2020. As Buera, Kaboski, & Shin (2021) note, loans by microfinance organizations represent a meaningful fraction of the GDP of several developing economies, such as Nicaragua (10%), Bolivia (9%), Kenya (3%), and Bangladesh (3%).
connections and establish repayment norms even with community peers with whom they do not share joint liability (Sanyal, 2009).

While the group lending approach has achieved remarkably high repayment rates overall (Cull, Demirgüç-Kunt, & Morduch, 2009), it has proven vulnerable to crisis conditions in the broader economic and social environment. For instance, natural disasters, such as the 2010 mass floods in Pakistan, and economic disruptions, such as the financial crisis in Nicaragua that followed the 2008 global financial crisis, have been followed by widespread defaults in many borrower communities (Guérin, Labie & Servet, 2015). Research has mainly attributed such mass defaults under crisis conditions to individual client-level factors, such as the innate vulnerability of poor borrowers and the riskiness of informal enterprises in which microloans are often invested (Ghosh, 2013) and, in some cases, the over-promotion of loans by growth-focused microfinance firms prior to the crisis (Haldar & Stiglitz, 2016). An alternative explanation, however, is that the lending communities organized by microfinance lenders—understood as essential to the promotion of loan repayment—might also contribute to the vulnerability of the group lending model to crises. Yet we have little empirical evidence regarding the extent to which microfinance defaults in crises relate to community-level processes, nor the specific role formal and informal social connections between borrowers might play (Giné, Krishnaswamy, & Ponce, 2011).

We explore this idea through empirical analysis of proprietary loan repayment data obtained from a large, for-profit Indian microfinance organization comprising approximately two million borrowers belonging to 430 thousand joint-liability groups, nested within 130 thousand community-level lending centers. We examine patterns of repayments during the nationwide crisis that followed India’s 2016 demonetization policy, which abruptly voided (without advance
notice) the legal status of all major (500 and 1,000 rupee) currency notes in circulation. Demonetization removed 87 percent of cash value in circulation in India’s heavily cash-dependent economy, leading to widespread economic disruption and distress (Chodorow-Reich, Gopinath, Mishra, & Narayanan, 2020; Natarajan, Mahmood, & Mitchell, 2019). Among the borrowers in our data, all of whom were female, the missed payment rate increased almost twenty-fold: from just two percent in the month before demonetization to about 40 percent in the month of demonetization. Our goal in this study is to document community-level patterns of microfinance loan defaults during the crisis, and to then explore the possible role of social connections.

Our first set of analyses looks for evidence of community-level clustering in the distribution of loan defaults across centers. To do so, we follow prior research by employing a “shuffle test” approach that compares local clustering in the observed pattern of defaults with a simulated counterfactual in which localization is incidental (Alcácer & Zhao, 2016; Aral, Muchnik, & Sundararajan, 2009). We implement this approach in our setting by first separating our data into over 3,000 small geographic areas, then comparing the clustering observed within each of those areas with a counterfactual scenario generated by randomly reassigning defaults across borrowers within that area. The results of this shuffle test indicate that loan default behavior was indeed significantly more localized within communities than would be expected in the absence of community-level factors.

This clustering suggests community-level processes played a significant role in determining defaults but does not allow us to differentiate between underlying pressures within communities that shaped individual borrower decisions. In a second set of analysis, we therefore used

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2 We use the terms “missed payment” and “loan default” interchangeably in this paper, while acknowledging that the term loan default is sometimes reserved only for cases where a borrower has missed payments several times in a row.
regression models at the individual-level to examine various explanations of the observed clustering, which include the formal economic interdependence associated with joint liability and informal peer influence. These models distinguish between “joint-liability” peers with whom a borrower shares legal joint-liability for loans, and “non-joint-liability” peers who belong to the same lending center but not the same joint-liability group as the focal borrower. We find that borrowers having a greater number of peers defaulting in the month of demonetization were indeed more likely to default in subsequent months, and that this effect was similar when considering defaults by joint-liability peers versus defaults by non-joint-liability peers. In further analysis, we also examine how these effects may differ for peers who belong to the same versus different religion as the focal borrower—a strong proxy for social solidarity in this context (Munshi & Myaux, 2006). The findings from this analysis indicate that a shared religion among peers is associated with greater influence for non-joint-liability peers but not for joint-liability peers, a finding consistent with the presence of significant informal influence that extends beyond the effects of formal joint-liability.

Overall, our study presents new evidence of community-level clustering of microfinance defaults under crisis conditions, a pattern that appears to be associated with not only formal joint-liability relationships between borrowers but also their informal social connections. While the group lending approach is widely celebrated for its use of social connections to facilitate financial access under stable conditions, these findings offer a useful reminder that such connections may have adverse business effects in times of crisis. More generally, our findings reinforce the outsized importance of informal connections and social influences, beyond formal contracts, in shaping the performance of firms that operate in emerging markets.

2. GROUP LENDING AND LOAN DEFAULTS UNDER CRISIS CONDITIONS
We begin by reviewing prior literature that considers the determinants of microfinance loan defaults under crisis conditions. We start with a brief introduction of the literature on group lending in general. We then discuss the aspects specifically relevant to crisis conditions, and how the loan default patterns might be shaped by formal as well as informal social connections within communities.

2.1. Loan Repayment in Group Lending
Group lending refers to the use of persistent, localized communities of borrowers to conduct microfinance loan disbursement and administration. Traditionally, group lending is associated with the use of joint-liability contracts that make borrowers accountable for the timely repayments of a fixed set of peers (Besley & Coate, 1995). Joint liability creates economic incentives for borrowers to engage in practices that decrease their jointly liable peers’ defaults, including screening of peer borrowers and monitoring of peers’ post-loan efforts to repay (Armendáriz & Morduch, 2010; Roodman, 2012; Stiglitz, 1990). The approach thus enlists borrowers to pressure each other into timely repayment, thereby overcoming limitations associated with weak institutions for contract enforcement and the lack of collateral or credit history that typically support traditional lending (Khanna, 2018).

Group lending is typically conducted through a nested structure in which each borrower belongs to a formal joint-liability group (JLG), and multiple JLGs are combined to form a single lending “center” to serve the local community. Lending activities are conducted at the center level, through regular meetings attended by a representative from the firm (typically called a “loan officer”). In addition to the routine activities of loan administration (i.e., origination and repayment), center meetings are typically designed to reinforce norms of personal support (Sanyal 2009, 2015), financial stewardship, and mutual accountability (Banerjee & Duflo, 2011; Bu & Liao, 2022; Feigenberg, Field, & Pande, 2013; Khanna, 2018), even among borrowers who
do not share joint-liability.³ Recent studies suggest that informal, non-joint-liability connections are also useful for promoting loan repayment (de Quidt et al., 2016), and may sometimes be sufficient to achieve high repayment rates even in the absence of formal joint-liability. For instance, Giné and Karlan (2014) find that randomized removal of the formal joint-liability clause in group lending did not significantly decrease repayment rates, suggesting that—at least in their context—informal relationships were sufficient to sustain high levels of repayment (see also Attanasio, Augsburg, De Haas, Fitzsimons, & Harmgart, 2015).

2.2. The Role of Formal Joint-liability under Crisis Conditions
Despite the consistently low default rates achieved by group lending under normal conditions (Banerjee, 2013; Cassar, Crowley, & Wydick, 2007; Karlan, 2007), spikes in defaults have been observed during crisis conditions driven by natural, economic, or political factors, sometimes even leading to complete breakdowns of the lending operations (Breza & Kinnan, 2021; Guérin et al., 2015; Tantri, 2018). But limited empirical evidence exists regarding the exact patterns of loan defaults and the specific role of social connections in the spread of crisis-induced defaulting behavior even among borrowers connected via joint liability (Giné et al., 2011). Therefore, before turning to the role of informal (non-joint-liability) peer connections, we first lay out arguments regarding how formal (within-JLG) jointly-liability can be expected to affect defaulting behavior.

Through the joint-liability mechanism, group lending uses the threat of peer default to incentivize borrowers to pressure their peers to repay. Yet when actual defaults occur, joint liability may adversely affect borrower incentives for repayment. That is, theoretical models

³ Our description here is representative of the mainstream microlending approach that was popularized by Grameen Bank. Although some microfinance organizations now do engage in group lending without formal joint-liability, most (including our partner form) continue to use a combination of formal and informal relationships (de Quidt, Fetzer, & Ghatak, 2016).
predict that under joint liability, defaults by jointly-liable peers might increase an individual borrower’s repayment burden, and thus their cost of remaining compliant (Besley & Coate, 1995). This mechanism has limited influence under normal conditions, as defaults are rare. However, when an external crisis leads to a short-term spike in defaults, the spillover effects of these defaults on peers who share joint liability may be substantial, as a greater extent of loan default among joint-liability peers could lead to an increase in the focal borrower’s subsequent likelihood of default.

2.3. The Role of Informal (Non-Joint-Liability) Peer Connections under Crisis Conditions
The empirical microfinance literature offers little insight into the role of non-joint-liability social connections in driving loan default patterns under crisis conditions. This is despite a growing body of broader research from non-microfinance settings that points to informal social relationships as often being a key factor in the spread of crises. For instance, Greve and Kim (2014) show that contagion in late-19th century bank runs was stronger in more demographically homogenous cities, arguing that interpersonal similarity among borrowers facilitated the spread of fear that banks would collapse. Similarly, Iyer and Puri (2012), studying account holder-level data from a run on a bank in India, use data on client referrals to demonstrate that defaults were transmitted via existing peer relationships (see also Brown, Trautmann, & Vlahu 2016). Analogously, Gupta (2019) studies the mortgage loans market during the 2008 financial crisis, and finds evidence that the contagion of defaults among geographically proximal borrowers was driven by the spread of information related to lender enforcement and the stigma associated with default.

In explaining how informal connections hasten the spread of crises, studies frequently focus on the spread of information about the crisis itself, and thus the consequences of behaviors that typically are counter-normative (e.g., loan defaults). Research across fields has suggested that
individuals rely heavily on social information in formulating their actions, particularly under crisis conditions where alternative information sources are sparse or unreliable. Economics research suggests that rational actors follow the behaviors of others when faced with limited information regarding the consequences of their actions (e.g., Hirshleifer, 2020), and often turn to specific relationships to guide action when norms break down (Lin, Prabhala, & Viswanathan, 2013; Sjöstrand, 1992). Psychology research has similarly long noted that when generalized norms of conduct are unavailable or unreliable, individuals often turn to relational social comparison for information about appropriate behavior (Festinger, 1954). Finally, sociologists have also noted that social actors rely heavily on existing relationships to make sense of crises (Weick, 1995), in part because the actions of familiar others are most salient and interpretable (Podolny, 1994).

Applied in the context of group lending, such informational diffusion during crises points to the possibility of the spread of defaults via informal social relationships beyond just joint liability: peers’ defaults are likely to convey information about beliefs regarding penalties that govern repayment, which include enforcement actions by the lending firm and social penalties (or withdrawal of support) from other borrowers. That is, in the uncertainty surrounding a crisis, peer defaults might affect a borrower’s own expectations about whether their own default would be met with punishment, either through formal contract enforcement by the lending firm or through informal social sanctions from their peers.

In the sections that follow, we first introduce our empirical context for studying microfinance loan defaults during the 2016 Indian demonetization crisis, and document the associated center-level patterns of loan defaults in our data. We then empirically explore the possibility of formal as well as informal peer influence in the observed pattern of defaults.
3. RESEARCH SETTING, DATA AND EMPIRICAL APPROACH

3.1 India’s 2016 Demonetization Policy

At 8 p.m. on November 8, 2016, Indian Prime Minister Narendra Modi announced the invalidation of all 500 and 1,000 rupee currency notes, or 87 percent of the currency in circulation, with the stated goal of curbing illegal commerce (Chodorow-Reich et al., 2020; Lahiri, 2020). The policy was announced via a surprise address televised simultaneously nationwide, and the policy (henceforth referred to as “demonetization”) went into effect at midnight the same day (Natarajan et al., 2019). In the same communication, the government announced that the affected currency notes could be exchanged for new and valid currency notes at formal financial institutions. However, extended delays in the printing and distribution of new bills, as well as daily per-person exchange limits, severely limited the availability of replacement notes for several months (Chodorow-Reich et al., 2020). Demonetization thereby dramatically reduced the liquid assets of a large majority of Indian households for an extended period (Banerjee, Breza, Chandrasekhar, & Golub, 2023; Chakravorti, 2017).

Empirical research has documented the broad and immediate impact of demonetization on economic activity across India. For instance, one study conservatively estimates that various types of economic activity were reduced by two percent in the fourth quarter of 2016 (Chodorow-Reich et al, 2020). Such effects are likely to have been particularly acute among microfinance borrowers, who are relatively poor and operate in informal sectors that rely heavily on physical currency (Collins, Morduch, Rutherford, & Ruthven, 2009). As one expert put it, “Liquidity has been sucked out. You have stopped market transactions for 70 percent of the

4 These currency notes were equivalent to about $7.5 and $15, respectively (Chodorow-Reich et al., 2020: 62). The total value of demonetized notes in circulation was approximately $230 billion, or about one-tenth of India’s GDP as of 2016. The government’s stated goals for demonetization were: (1) eradication of “black money”, (2) removal of counterfeit notes, (3) curtailment of terrorism funding, and (4) encouraging move to a digital economy (Sanyal, 2018).
economy. The poor will suffer more.” (Sanyal, 2018: 39). A borrower’s choice to pursue a microfinance loan may furthermore indicate their lack of financial liquidity, and therefore their vulnerability to a liquidity crisis.

3.2 Borrower-Level Data from a Microfinance Firm
Our study relies on proprietary, borrower-level repayment data obtained from a large Indian microfinance firm engaged in group lending (not named here due to a non-disclosure agreement). At the time of data collection, the firm engaged in group lending in 15 of the 29 Indian states, and lent exclusively to individuals identifying as women.5 Our dataset covers the 2,036,108 borrowers who had active loans with the firm at the time of demonetization (November 8, 2016), and includes their full repayment records from July 2016 to February 2017 (inclusive), as well as the borrower demographics and their loan characteristics as recorded in the firm’s database.

Our partner firm’s organization, borrower demographics, and group lending procedures were typical of the Indian microfinance industry. An assigned loan officer collected repayments at lending center meetings. These mandatory meetings followed a standard agenda that included not just the formal collection of due payments, but also informal activities like the collective sharing of recent successes and learnings from each borrower’s experience.6 In line with prior studies pertaining to microfinance lending (e.g., Canales, 2014), loan terms were highly standardized: nearly all borrowers received initial loans of 25,000 rupees (approximately 375 USD), to be repaid in regular installments due once every two weeks over a duration of two years. No collateral was involved. Upon repayment of their loan balance, borrowers with strong

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5 Combined, these 15 states contained over 70 percent of India’s total population and almost 75 percent of the total rural population. The firm operated primarily in North and Central India and was not implicated in the 2010 microfinance crisis that originated in the South Indian state of Andhra Pradesh.
6 We were not provided access to the raw data due to concerns that doing so might reveal too much sensitive information. Instead, by signing a confidentiality agreement, we did manage to obtain access to the data as aggregated to the monthly level (which the firm has to prepare for mandatory reporting to a government agency).
repeated records were generally offered an opportunity to take a new, larger loan: at the time of demonetization, 68% of the borrowers in our dataset were in their first loan cycle. In terms of borrower characteristics, our sample appears similar to those studied in prior microfinance research (Banerjee, Chandrasekhar, Duflo, & Jackson, 2013; Bulte, Lensink, & Vu, 2017; Canales, 2014; Karlan & Zinman, 2011).

In order to comply with Indian regulatory requirements for microfinance institutions, only individuals with a monthly household income of 12,000 rupees (180 USD in November 2016) or less were eligible for a loan from the firm. Borrowers were recorded as being primarily engaged in one of 13 unique occupations, such as agriculture, handicraft, repairs, retail, and weaving. They ranged from 17 to 62 years of age, with the mean age being 37 years. The two largest religious groups represented among borrowers were Hindus (72%) and Muslims (17%), a distribution similar to national averages (80% and 15%, respectively). Sikhs were over-represented relative to national statistics (11%, compared with 2% nationally), while Christians were under-represented (<1%, compared with 2% nationally).

Figure 1 shows the organizational structure of the microfinance firm’s operations. There were 536 regional branches, each serving borrowers within a geographic area of approximately 25 kilometers (15.5 miles) in radius. Each branch employed an average of 5.7 loan officers (also known as “community service officers”), with a loan officer managing an average of 43.1 lending centers (“centers”) within close geographic proximity of a few square kilometers. Each center corresponded to a small geographic and social unit of borrowers, typically one large village or a few small neighboring villages, and contained an average of 15.5 borrowers.

Borrowers within a center were further divided into smaller “joint-liability groups” (JLGs) (average size: 4.7 borrowers). As per the loan agreement, borrowers were only legally liable for
the repayment of their own loans and loans held by peers within their joint-liability group; however, we found these boundaries to be generally invisible during center-level meetings. 

During field visits, we observed center meetings, in which loan officers led community-building routines in line with previously documented practices by which microfinance lenders often reinforce social capital and “solidarity” among borrowers within a center (Khanna, 2018: 108). Interviews with loan officers and borrowers themselves confirmed that all activities were conducted at the center level, and that JLG boundaries were rarely acknowledged in the administration of loans. For instance, the collection of repayments at the center meeting was deliberately carried out in full view of all borrowers so that each borrower’s repayment status was visible to all other borrowers—not only those within her JLG group. At each meeting, the borrowers were always asked to recite the following oath (following a standardized script) together, pledging their commitment to adhering to the norms expected of all center members and working towards ensuring the success of all borrowers from their center:

“We take a pledge that we shall attend the center meetings without fail. We shall pay back all the loan instalments on time. We shall help the needy in our center, whenever required. All the center members will abide by the rules and responsibilities of the center. We shall use the loan amount taken to uplift our family

7 JLG co-membership was also not very consequential practically in terms of formally pursuing loan repayment from other JLG members in the event of a default by the focal borrower. As the company official shared with us, pursuing legal enforcement of JLG contracts in Indian courts was just not an efficient or financially worthwhile means of collection given the small loan amounts involved. Therefore, in reality, if a borrower did miss her repayment, the loan officer simply recorded it as a missed payment from only that borrower, and a poor repayment track record meant an increased chance of ineligibility of the individual borrower to receive future loans from the microfinance firm.

8 To avoid confounding informal peer influence with formal joint-liability effects, our analyses of individual repayment decisions (see Section 5) separately estimate the peer influence between borrowers who were part of the same lending center but not the same JLG and the peer influence between borrowers who were part of the same JLG. Admittedly, the relative importance of JLG-level (formal) drivers and center-level (informal) drivers of loan repayment rates could differ across microfinance institutions, a caveat that needs to be borne in mind when interpreting our findings.
condition. We shall neither accept nor offer any commission to center members, staff, and others.”

3.3. Empirical Approach for Examining Loan Defaults within Lending Centers
Following prior research examining microfinance loan repayment (Canales & Greenberg, 2016; Doering, 2018), we set a binary variable Missed Payment to one if a borrower failed to make a scheduled payment in a given month, and to zero otherwise. As expected, the overall rate of missed payment increased dramatically in the month of demonetization and remained high in the following months: the monthly default rate of 1-2% in the four months prior to demonetization (July to October 2016) increased to 39% in the month of demonetization (November 2016), and further to 44-46% in the three months that followed (December 2016 to February 2017).9

We conduct two complementary sets of empirical analysis to examine the observed pattern of loan defaults in relation to the demonetization crisis. The first examines center-level differences in the average rate of missed payment, and tests the possibility of clustering of missed payments among borrowers within lending centers. To conduct this analysis, we draw upon prior research that has relied on the geographic localization of individual-level outcomes as indirect evidence at least consistent with the presence of social influence among co-located economic actors (Jaffe, Trajtenberg, & Henderson, 1993; Alcácer & Zhao, 2016). Specifically, we examine the degree of

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9 Figure S1 in the supplementary material breaks up the missed payment pattern further for borrowers living in brick houses (indicative of the poverty level not being too severe: about one-third of our borrower sample) versus non-brick houses (indicative of more severe poverty: about two-thirds of our borrower sample). Prior studies from similar contexts have also often used such proxies for poverty levels, especially as income data is typically self-reported and unreliable even when available (Alatas, Banerjee, Hanna R, Olken, & Tobias, 2012; Bandiera et al., 2017). In pre-demonetization months, borrowers living in non-brick houses were only slightly more likely to miss payment than those living in a brick house, but this gap increased substantially beginning in the month of demonetization, consistent with a view that demonetization more adversely affected the repayments of poorer borrowers who were already in a more tenuous economic situation.
clustering of missed loan payments within lending centers. Our second set of analysis uses individual-level regression models to examine whether the loan default patterns are consistent with the presence of peer influence affecting loan repayment by individual borrowers. Specifically, we estimate the extent to which the repayment behavior of peers in the month of demonetization (November 2016) predicts the focal borrower’s likelihood of default in subsequent months. In doing so, we disentangle the evidence of joint-liability versus non-joint-liability peer influence.

A central challenge in our analyses is the possibility of unobserved factors that could have driven missed payments during the crisis. Loan defaults may have been influenced by multiple factors that varied across geographies, such as the speed with which the Reserve Bank of India sent new currency notes to a region, the ease with which people from the region had access to banks or ATM machines where new notes were dispensed, and the extent to which the region’s economy relied on cash in the first place. Borrowers also interacted with distinct loan officers with different relational styles, a factor shown by prior research to influence repayment (Canales & Greenberg, 2016). Because we are unable to observe all such factors directly, we utilize statistical approaches that account for, to the greatest degree possible, unobserved heterogeneity in factors that might vary by geography. In particular, in both center-level and individual-level analyses, we compare missed payment rates only across centers belonging to the same “loan officer area”—the relatively circumscribed area covered by the same loan officer (see Figure 1). This approach controls for unobserved heterogeneity in explanatory factors that might drive

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10 Rather than relying just on center co-membership, we would have liked to have a more direct measures of social ties, such as via network data collected through surveys (Guiso, Sapienza & Zingales, 2013). Unfortunately, such data collection was impractical in our setting. Nevertheless, as explained later, we do try to capture at least some of the differences in the strength of social ties within a center, namely, having a shared religion.

11 Because we are constrained by our data being monthly, we are unable to test relational influence within a given month. Given this constraint, our investigation focuses on month as the temporal unit of analysis.
differences in missed payments between areas served by different loan officers. While we acknowledge that this might not perfectly account for unobserved heterogeneity across centers (e.g., as even neighboring centers can be different in local economic conditions), it does mitigate the potential influence of geography-related unobserved heterogeneity on our findings.

4. CENTER-LEVEL ANALYSIS OF CLUSTERING OF LOAN DEFAULTS

As previously described, the overall rate of missed payments increased suddenly from two percent in the month before the crisis to nearly forty percent in the month of demonetization (see Figure 2). If within-center social influence were one of the important contributors to this jump, we would expect it to have magnified differences in the incidence of default across centers.

A simple but coarse indicator of this center-level clustering is the appearance of either a 100% or 0% repayment rate within a center. In the pre-demonetization period, over ninety percent of all the centers in our data were “full collection centers” (where all of the local borrowers repaid), and less than one percent were “zero collection centers” (where none of the local borrowers repaid) (see Figure 3). In sharp contrast, following demonetization, the fraction of lending centers that became zero collection centers exceeded 20 percent. This jump is suggestive of localized influence—post-demonetization—in borrower decisions to default.

[Insert Figure 3 here]

To refine our measurement of clustering, we adopt an empirical strategy sometimes called the “shuffle test” (Alcácer & Zhao, 2016; Aral et al., 2009; Christakis & Fowler, 2007), a special form of “placebo” test (Athey & Imbens, 2017) that compares the pattern of actual outcomes with a simulated counterfactual generated by reassigning those outcomes across individuals. This kind of inferential strategy is well-established in literature pertaining to economic geography, such as studies examining geographic clustering in the context of industrial activity (Ellison & Glaeser, 1997) or knowledge spillovers (Jaffe et al., 1993). In our setting, we construct a
counterfactual by randomly reassigning defaults among borrowers, thus creating a scenario in which the overall rate of default is identical to the actual data but in which defaults are unrelated to the boundaries of lending centers. We then measure clustering by comparing the concentration of defaults within centers in this counterfactual to that which is observed in the actual data.

To address geographic heterogeneity in factors that might influence missed payments, we implement our reassignment at the level of the loan officer area. In other words, we conduct 3,037 separate shuffles, one for each of the 3,037 loan officers and their corresponding coverage areas. Recall that loan officer areas contain an average of 43 lending centers (see Figure 1) in a small geographic area of a few square kilometers. Conducting a separate “shuffle” for each loan officer area helps address concerns that unobserved heterogeneity across loan officers, or the geographic and economic conditions in their respective coverage areas, might also affect loan defaults. To ensure the robustness of our counterfactual, we repeat the process and take the average of center-level default rates across 10,000 permutations of the simulation described above for centers belonging to each of the loan officer areas.

Figure 4 compares the kernel density distributions of center-level default rates in our actual data versus in the simulated counterfactual. Panels A-C of Figure 4 correspond to October 2016 (the month before demonetization), November 2016 (the month of demonetization), and December 2016 (the month after demonetization), respectively. The actual data exhibit strikingly

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12 A loan officer area is the smallest administrative unit that allows for center-level variation. As Figure 1 shows, this is much more granular than the next-highest level of branch, which covers an average radius of 25 kilometers (15.5 miles) and is further subdivided into about six loan officer areas, or a state, which contains many branches.

13 Note that the counterfactual generated by randomly reassigning missed payments among borrowers within a loan officer area (for a given month) by construction has exactly the same overall number of missed payments as the original data for any given loan officer area (for that month)—the only difference is in how these defaults are distributed within the loan officer area. We should acknowledge that data limitations prevent our research design from accounting for any differences that might still remain across centers located within the same loan officer area.

14 While variation in results across multiple permutations was limited, we conducted 10,000 permutations to ensure a stable distribution.
fat tails at the left and right ends of the distribution in November 2016, indicating that lending centers were much more likely to have either very high or very low default rates in reality versus in the simulated counterfactual, in which most centers had more moderate default rates. This overall pattern is indicative of large post-demonetization differences in loan default outcomes across centers even within the same loan officer area, consistent with a meaningful role for social influence in determining the pattern of defaults across centers.\textsuperscript{15}

To summarize, our center-level analysis indicates that increased missed payments post-demonetization are disproportionately clustered within some centers. However, it does not provide insight into the exact mechanisms driving these patterns, which could include regional heterogeneity, economic co-dependency from joint-liability connections, and peer influence from non-joint-liability connections.\textsuperscript{16} Therefore, in the next section, we offer a more fine-grained individual-level analysis that explores the consistency of our data with peer influence through formal (joint-liability) connections and informal (non-joint-liability) connections.

5. INDIVIDUAL-LEVEL ANALYSIS OF LOAN DEFAULTS

In this section, we estimate a borrower’s choice to default in post-demonetization months (December 2016-February 2017) as influenced by the default decisions of her peers (to whom she is either formally or informally connected) in the month of demonetization (November

\textsuperscript{15} Formal Kolmogorov-Smirnov tests reject the hypothesis that the actual and simulated data have the same underlying distribution for any of the months, October 2016 ($D = 0.77$, $p < 0.001$), November 2016 ($D = 0.33$, $p < 0.001$), or December 2016 ($D = 0.28$, $p < 0.001$). Furthermore, a similar test suggests that actual patterns for November 2016 and December 2016 do not have the same distribution function ($D = 0.09$, $p < 0.001$), with December 2016 showing an even fatter tail at the right end of the distribution. Similar patterns are observed if we plot the histograms depicting the frequency distribution of borrowers with missed payments rather than drawing kernel density plots. Figure S2 in the supplementary material provides histograms for all months in our data.

\textsuperscript{16} It is important to note that our shuffle test only compares centers in close geographic proximity and served by a single loan officer. Therefore, this clustering is unlikely to be driven by loan officer or corresponding geography-specific differences, and hence seems likely to be driven by localized influence operating at the center level.
2016). Our analysis consists of two main steps: (i) estimating separately the influence of formal, joint-liability and informal, non-joint-liability relationships; and (ii) estimating the degree to which stronger ties—indicated by a shared religion between two borrowers—may magnify these effects and shed further light on the possibility of different kinds of peer influence.

5.1. Estimating Loan Defaults under Crisis Conditions
We estimate individual-level regression models that predict loan defaults at the borrower level. For robustness, we employ two different dependent variables: Missed Payment (Dec16-Feb17), an indicator for missing one or more loan payments in the three months following the month of demonetization, and Missed Payment (Dec16), an indicator for missing one or more payments in the single month immediately following the month of demonetization.\(^{17}\) Importantly, all models include a variable that captures whether or not the focal borrower had already missed a payment in the month of demonetization itself (November 2016), and thus control for the immediate impact of demonetization on the borrower herself. All models also employ standard errors clustered at the center level. The formal regression equation, which employs a linear probability model to minimize functional form dependency, is as follows:\(^{18}\)

\[
\text{Missed Payment (Dec16-Feb17)}_i = \alpha + \beta_1 \text{Same-JLG Peers Missed Payment (Nov16)}_i + \beta_2 X_i + \gamma \text{Loan Officer Area} (i) + \varepsilon_i
\]  

\(^{17}\) Analysis of peer influence faces the “reflection problem” arising from simultaneity (Manski 1993a, 1993b). In order to mitigate associated concerns, we follow prior studies (Blume et al., 2015; Reza et al., 2021; Hanushek, Kain, Markman, & Rivkin, 2003) that recommend estimating the influence of peers on future behavior, while controlling for individual-level characteristics. This approach has been applied in several contexts, including product diffusion (Iyengar, Bulte, & Valente 2011) and neighborhood bankruptcies (Agarwal, Mikhed, & Scholnick, 2020). Our regression analysis most closely follows the linear social interaction models recommended by Blume et al. (2015).

\(^{18}\) Recent work has emphasized the benefit of a linear probability model when employing fixed effects (e.g., Bennett et al., 2013: 1733) as these do not suffer from the incidental parameters problem like non-linear models do (Wooldridge, 2002: 454-457; Angrist & Pischke, 2009). In any case, our main findings are robust to employing logistic regressions. The formal estimation equation (1) is shown using only Missed Payment (Dec16-Feb17) for brevity as the right-hand side of the equation for the alternate dependent variable Missed Payment (Dec16) is identical.
The estimator $\beta_1$ represents the effect of *Same-JLG Peers Missed Payment (Nov16)*—the number of peers within the focal borrower’s joint-liability group who missed payment in November 2016—on *Missed Payment (Dec16-Feb17)*. An important feature of this specification is the inclusion of loan officer area fixed effects, $\gamma_{\text{Loan Officer Area (i)}}$, to control for unobserved heterogeneity across loan officer areas that might also drive default rates (Angst, Agarwal, Sambamurthy & Kelley, 2010; Canales & Greenberg, 2016; Doering, 2018). Table 1 provides formal definitions and summary statistics for all of our variables.

[Insert Table 1 here]

Column 1 in Table 2 reports the results based on estimation equation (1) in its simplest form. The coefficient of *Center Peers Missed Payment (Nov16)* is positive ($\beta = 0.0105$, 95% CI [0.0096, 0.0114], $p = 0.000$). This finding suggests that a borrower is more likely to miss payments when other borrowers in their joint-liability group had previously missed a payment.

[Insert Table 2 here]

Subsequently, we analyze whether missed payments by a borrower’s non-joint-liability peers (belonging to the same center but not the same JLG) influence her subsequent likelihood of missing a payment. We start with a model that is practically identical to equation (1), but uses *Different-JLG Peers Missed Payment (Nov16)* in place of *Same-JLG Peers Missed Payment (Nov16)* as the explanatory variable. Column 2 in Table 2 reports a positive peer influence even in this case ($\beta = 0.0077$, 95% CI [0.0073, 0.0082], $p = 0.000$), suggesting that a borrower is more likely to miss payments when more of her non-joint-liability peers previously miss a payment.

Our preferred regression specification combines *Same-JLG Peers Missed Payment (Nov 16)* as well as *Different-JLG Peers Missed Payment (Nov 16)* as explanatory variables in a single model. In this more complete specification, reported in Column 3 of Table 2, the coefficients on both explanatory variables are slightly diminished relative to Columns 1 and 2, but remain
positive. Although the magnitude of joint-liability peer influence appears larger than that of non-joint-liability peer influence, the difference between the two coefficients is statistically indistinguishable from zero (Wald test \( F = 0.93, p = 0.334 \)).

In terms of economic significance, the estimated coefficient of *Same-JLG Peers Missed Payment (Nov 16)* in Column 3 implies that increasing missed payments by joint-liability peers in November 2016 by one standard deviation increased the focal borrower’s subsequent probability of missed payment by 4 percent. Similarly, the estimated coefficient of *Different-JLG Peers Missed Payment (Nov 16)* in Column 3 implies that increasing missed payments by non-joint-liability peers in November 2016 by one standard deviation increased the focal borrower’s subsequent probability of missed payment by 7.4 percent.

Columns 4-6 in Table 2 re-estimate these models with our alternate (one month) dependent variable *Missed Payment (Dec16)*, and show results qualitatively similar to Columns 1-3. In the full specification (Column 6), the estimated magnitude of the influence of joint-liability peers is once more slightly larger than that of non-joint-liability peers, with the difference between the two coefficients now being statistically stronger (Wald test \( F = 4.25, p = 0.039 \)).

### 5.2. Further Analysis of Potential Peer Influence

Thus far, we have found that default by a greater number of a borrower’s peers, of both joint-liability and non-joint-liability types, is associated with a higher likelihood of the borrower’s own subsequent default. If peer influence is a potential mechanism driving the effect of non-joint-liability peers, one should observe that this effect is stronger for the subset of peers with whom the borrower is connected through stronger social ties. While we lack the interactional

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19 We also explored the possibility of threshold effects rather than a linear relationship in how a borrower’s behavior is influenced by the number of peers previously engaged in that behavior (Granovetter, 1978). This analysis involved “binning” the number of peers with missed payments into distinct categories to carry out non-parametric econometric estimation. The results, reported in Figure S3, do not find much evidence of a strong threshold effect.
data that would be needed to directly measure social ties, we infer the presence of such ties indirectly through the proxy of shared religion between borrowers.\footnote{Previous research suggests that membership in a common social group predicts both the frequency and quality of social interactions. Individuals belonging to such a group experience enhanced the level of generalized trust (Coleman, 1990), and in group lending specifically, enhanced trust among individuals has been shown to also enhance the intensity of peer monitoring (Karlan, 2007). Conversely, research in both organization theory (Burt, 2011; Hasan & Bagde, 2015; Reagans, 2011) and economics (Alesina & Ferrara, 2005; Easterly & Levine, 1997) notes that social heterogeneity can impede cooperation and coordination—which in group lending could ultimately lead to a reduction in the likelihood of collective behavior driven by peer influence.}

While religion is an important dimension of social distinction and social group membership in many societies, this is particularly likely to be the case in developing societies (Munshi, 2019). Intra-religious ties in such contexts can therefore be expected to be especially strong (and hence disproportionately responsible) for interpersonal influence in settings like ours. For instance, Munshi and Myaux (2006), studying the diffusion of family planning practices in Bangladesh, find that intra-religious connections explain virtually all of the social influence. Research in other settings has also found that social groups defined by religious identity shape individual behavior in other economic settings, such as in adherence to financial contracts (Yenkey, 2015) as well as observed outcomes in lending in contexts beyond microfinance (Fisman, Paravisini, & Vig, 2017). It is therefore reasonable to expect that, even in the context of group lending, social influence would be stronger among peers sharing a common religion than those belonging to different religions.

In line with the above arguments, we refine our previous regression model by further dividing the focal borrower’s peers into four mutually exclusive and exhaustive categories defined by differences on two dimensions: (i) joint-liability versus non-joint-liability peers, and (ii) same religion versus different religion peers.\footnote{It is worth noting that the assignment of individuals to joint-liability groups might not be completely random. For example, it is possible that religion is at least partly a consideration when individuals are getting sorted into JLGs. This caveat needs to be borne in mind when interpreting the findings from our religion-related analyses.} For clarity, we once more first introduce the
variables in separate specifications in Columns 1 and 2 of Table 3, before going on to our preferred specification that combines the two in Column 3 of Table 3. Column 1 includes the two components based on a common religion or not for the same-JLG peers, and finds very similar estimates for the same-religion and different-religion peers (Wald test F = 0.79, p = 0.374). Column 2 includes the two components based on a common religion or not for the different-JLG peers, and finds the same-religion peers to exert a slightly larger influence than different-religion peers (Wald test F = 22.92, p = 0.000). Column 3 reports the full model with all four indicators now included together, but the estimates still lead to an interpretation that remains qualitatively similar to those obtained from Columns 1 and 2. Our key findings from Column 3 also continue to hold when we employ our alternate dependent variable, as reported in Column 6.

Taken together, these results suggest that membership in the same religious group significantly amplifies the influence of informal, non-joint-liability connections but not of formal, joint-liability connections. This finding is consistent with the idea that the mechanism underlying the effect of joint-liability connections is primarily based on economic factors (i.e., the increase in liability resulting from their peers’ defaults), whereas the influence of non-joint-liability connections is based to a greater degree on informal social sanctions among peers.

[Insert Table 3 here]

6. EXPLORATORY ANALYSIS OF CROSS-CENTER HETEROGENEITY
In this section, we report further analyses that shed light on factors likely to be driving the observed loan default patterns, focusing especially on possible cross-center differences.

6.1. Differences in Pre-Demonetization Repayment Rates across Centers
In line with the view that repayment rates in group lending are governed not just by fear of reprisal by specific peers but also by overall center-level norms (Haldar & Stiglitz, 2016), we considered whether the observed effects might be shaped by persistent center-level norms that
existed even prior to the crisis. To accomplish this, we use differences in pre-demonetization loan repayment rates across centers as a proxy for cross-center differences in these norms.

Specifically, we define a new indicator 100% Repayment Center (PreNov16) as 1 for borrowers belonging to centers that had perfect repayment in the three pre-demonetization months (88% of borrowers), and to 0 for the remaining borrowers (12% of borrowers). We then estimate individual-level models similar to those used earlier, but now distinguishing between borrowers based on 100% Repayment Center (PreNov16). The findings, reported in detail in Table S1 in the supplementary material, suggest that the association in default rates among borrowers does indeed seem stronger in centers with perfect repayment rates pre-demonetization—evidence consistent with the presence of persistent center-level norms.22

6.2. New Centers versus Old Centers

We further explore whether the effect of peer influence may be different for relatively new centers (defined as those where all borrowers are in their first loan cycle) versus those that have operated for longer (with the borrowers in multiple loan cycles together). New centers might differ from longer-established centers on multiple dimensions, including the strength of social connections between borrowers and that of the relationship of the focal borrower with the lending firm. We create a new variable, New Center, set to 1 for borrowers in centers where all borrowers were in their first cycle as of the time of the demonetization policy announcement (49% of the borrowers belong to a new center), and to 0 otherwise (the remaining 51% of the borrowers). We again estimate models similar to those used earlier, but this time distinguishing borrowers from new versus old centers. The findings, reported in detail in Table S2 in the

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22 Specifically, considering our preferred (full specification) model results reported in Column 3 of Table S1, we note that the estimates for Same-JLG Peers Missed Payment (Nov16) × 100% Repayment Center (PreNov16) and Different-JLG Peers Missed Payment (Nov16) × 100% Repayment Center (PreNov16) are both positive, indicating that the influence of both JLG and non-JLG peers was larger in centers with 100% repayment pre-demonetization.
supplementary material, suggest that the peer influence among borrowers was at least as strong (in fact stronger) in the new centers when compared with the older centers.\textsuperscript{23}

In sum, these supplementary analyses (in subsections 6.1 and 6.2) provide two useful insights. First, when center-level norms are stronger, we observe a greater effect of peer influence. It is important to acknowledge that economic co-dependency may also drive the link between stronger center-level norms and the observed greater effect of peer influence. Second, we observe a greater effect of peer influence in newer centers. This finding implies that it is important to consider that borrowers at older centers may not feel the need to follow their peers as much as those at newer centers, because the borrowers at older centers are more familiar with the lending firm. The uncertainty (in how the lending firm would respond to defaults) faced by borrowers in older centers is likely lower than that faced by borrowers in newer centers.

7. DISCUSSION AND CONCLUSION
In this paper, we have documented and empirically demonstrated an important vulnerability in the group lending model that is widely employed by microfinance firms in low-income communities around the world: under crisis conditions, where the risk of individual defaulting is already high, loan defaults may be further aggravated due to community-level clustering of behavior. We have further presented evidence consistent with both formal and informal social connections likely playing an important role in the spread of missed payments among borrowers under crisis conditions. Our analyses of patterns of missed payments by about two million clients of a microfinance firm following India’s 2016 demonetization policy indicate a high degree of clustering of defaults among socially connected borrowers. Further analysis of individual-level

\textsuperscript{23} Considering our preferred (full specification) model results reported in Column 3 of Table S2, we note that the coefficient estimates for the two relevant interaction terms, \textit{Same-JLG Peers Missed Payment (Nov16) \times New Center} and \textit{Different-JLG Peers Missed Payment (Nov16) \times New Center} are both positive and large, indicating support for the argument that the influence of both JLG and non-JLG center peers is materially larger in the new centers.
repayments suggests that not only a borrower’s joint-liability connections, but also her non-joint-liability connections, are important predictors of a borrower’s propensity to subsequently default.

Our research primarily intends to contribute to management research related to group lending and microfinance, a central thread in the growing interest of management researchers in business models designed to address social issues (Luo & Kaul, 2019). Past research in this area has predominantly focused on organization-level strategies, examining how differences in the business environment affect outcomes, including pro-social outreach (Wry & Zhao, 2018; Zhao & Wry, 2016), operating models (Ault, 2016; Ault & Spicer, 2014; Garmaise & Natividad, 2010), and resource acquisition (Cobb et al., 2016; Zhao & Lounsbury, 2016). While these studies have contributed to our understanding of microfinance organizations, a noteworthy subset of studies has underscored the significance of dyadic relationships between loan officers and borrowers as a key factor influencing lending outcomes (Canales, 2014; Canales & Greenberg, 2016; Doering, 2018). Our study also examines individual-level outcomes, but offers a distinct contribution by illuminating the role of social relationships between borrowers under crisis conditions. While prior research in other settings beyond microfinance suggests that social connections can hasten the spread of crises, research has not previously examined this relationship in the context of microfinance—despite the fact that both formal and informal social connections are a core component of the canonical group lending model. Our study fills this gap.

Informed by recent microfinance research (Attanasio et al., 2015; de Quidt et al., 2016; Giné & Karlan, 2014), our research presents evidence consistent with not only economic but also social relationships between borrowers in influencing repayment decisions under crisis conditions. The informal, social connections between borrowers have largely been overlooked in prior microfinance literature, which has primarily focused on formal, joint-liability connections...
between borrowers. By examining the role of economic and social connections between borrowers from the same community under crisis conditions, we contribute to the growing body of research that recognizes the importance of community-level factors in shaping the success of microfinance initiatives. Our study highlights that the community-lending strategy, representative of a practice relying on social exchange in general, may serve as a double-edged sword. Under normal conditions, it encourages timely loan repayments. Yet, our results suggest that, under times of crisis, the same social exchange-based mechanism can create adverse consequences for loan repayments. Our findings imply that a contingency perspective should be considered when making decisions about relying on social exchanges in microfinance contexts.

Our work also relates to the broader management literature that seeks to understand how adverse behaviors may spread among people who are socially connected (Chan, Chen, Pierce, & Snow, 2021; Greve, Kim, & Teh, 2016; Gupta, 2019), particularly when these connections serve a specific strategic purpose. The organized, center-level social interaction that is central to the group lending model provides an unusually attractive opportunity to analyze these issues. Heimer (2016: 3180) summarizes a challenge facing prior research on peer influence, noting that “hampered by data limitations, most empirical papers use creative proxies for peer interaction, such as background characteristics (Lerner & Malmendier, 2013) or geographic variation (Hong, Kubik, & Stein 2005).” In the studies of contagion on which we build, social relationships typically arise exogenously, e.g., from geographic proximity (Gupta, 2019) or demographic similarity (Greve et al., 2016; but also see Iyer & Puri, 2012). Our context, by contrast, directly identifies those peer relationships that have been reinforced strategically (often at significant cost) by a lending firm. Our study also contributes to research on peer influence by identifying membership in a common religious group as an important moderating factor. By disaggregating
the influence of same- and different-religion peers, our work joins the research stream studying how peer influence may vary as a consequence of variation in the nature of social ties (Agarwal, Qian, & Zou, 2021).

As in most empirical studies, features of our specific empirical context may limit the external generalizability of our findings. The borrowers in our data are numerous and representative of poor women in India, and the lending practices of our partner firm are similar to those of other microfinance firms in India and beyond. Nevertheless, our findings should be interpreted in the context of the particular characteristics of the lending firm’s culture, processes, and staff. The external validity of our findings to other crisis situations might also be limited by the specific setting of the 2016 demonetization policy: this shock represented only one among a variety of natural, political, and economic events that could drive repayment crises (Guérin et al., 2015, 2018), although we believe that its identifiable timing and acute effect on loan repayments does make it a useful setting to examine how a crisis affects group lending. As our focus has been to specifically examine the post-demonetization crisis and not in normal (stable) conditions, we do not intend to make any claims about the net overall effect for the microfinance firm, or for the society, of relying on the group lending business model.24

Certain features of our data limit our investigation of the mechanisms underlying the observed pattern of defaults. As the repayment data available to us has information only at a monthly level (even though actual repayment decisions occur every two weeks), we have been unable to examine within-month variation in outcomes. Given our inability to observe comprehensive and precise network data, we also had to use imperfect measures—center co-

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24 While defaults negatively affect the lending firm’s performance, they cannot be assumed to have an unambiguous net negative impact when also considering borrower well-being. Indeed, the choice to default may enable short-term spending that outweighs the negative consequences experienced through legal liability or reputational loss. While this issue is outside the scope of our study, we believe that it is an interesting and important direction for future research.
membership and sharing a common religion—to capture social connections. Also, while we have tried to account for unobserved heterogeneity as much as our data constraints allow (for example, by making inter-center comparisons only within a loan officer area), the non-random nature of center membership and the possibility of omitted variables that cause differences within loan officer areas prevents us from making conclusive causal claims.

Yet despite these limitations, we believe that our study offers new insight into the risks of reliance on social connections between borrowers within a community, a tactic shown to be of particular importance for reaching the global poor. We further hope that our work will encourage further research and practical insight into the robustness to crises of such strategies, in group lending and beyond.
REFERENCES
Agarwal S, Qian W, Zou X (2021) Thy neighbor's misfortune: Peer effect on consumption. American
Literature 43(3):762-800.
diffusion: The adoption of electronic medical records in US hospitals. Management Science
56(8):1219-1241.
Aral S, Muchnik L, Sundararajan A (2009) Distinguishing influence-based contagion from homophily-
driven diffusion in dynamic networks. Proceedings of the National Academy of Sciences
106(51):21544-21549.
Ault JK, Spicer A (2014) The institutional context of poverty: State fragility as a predictor of cross-
national variation in commercial microfinance lending. Strategic Management Journal
35(12):1818-1838.
Ault JK (2016) An institutional perspective on the social outcome of entrepreneurship: Commercial
Banerjee AV (2013) Microcredit Under the microscope: What have we learnt in the last two decades,
Banerjee AV, Breza E, Chandrasekhar A, Golub B (2023) When less is more: Experimental evidence
on information delivery during India's demonetization. Review of Economic Studies forthcoming
https://doi.org/10.1093/restud/rdad068.
341(6144):12364981–12364987.
Banerjee AV, Duflo E (2011) Poor Economics: A Radical Rethinking of the Way to Fight Global
Poverty (Public Affairs).
Blume LE, Brock WA, Durlauf SN, Jayaraman R (2015) Linear social interactions models. Journal of
Political Economy 123(2):444-496.
Breza E, Kinnan C. 2021. Measuring the equilibrium impacts of credit: Evidence from the Indian


Table 1. Definition of Variables for Individual-Level Analysis

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Missed Payment (Dec16-Feb17)</td>
<td>Indicator set to 1 if the borrower fails to pay the scheduled repayment in any of the three months from December 2016 to February 2017</td>
<td>0.52</td>
<td>0.50</td>
</tr>
<tr>
<td>Missed Payment (Dec16)</td>
<td>Indicator set to 1 if the borrower fails to pay the scheduled repayment in December 2016</td>
<td>0.46</td>
<td>0.50</td>
</tr>
<tr>
<td>Same-JLG Peers Missed Payment (Nov16)</td>
<td>The number of borrowers in the borrower's JLG, excluding the borrower herself, who fail to pay the scheduled repayment in November 2016</td>
<td>1.89</td>
<td>2.86</td>
</tr>
<tr>
<td>Different-JLG Peers Missed Payment (Nov16)</td>
<td>The number of borrowers in the borrower's center, excluding the borrower's JLG, who fail to pay the scheduled repayment in November 2016</td>
<td>4.73</td>
<td>5.74</td>
</tr>
<tr>
<td>Same-JLG Same-Religion Peers Missed Payment (Nov16)</td>
<td>The number of borrowers from the borrower's religion in the JLG, excluding the borrower herself, who fail to pay the scheduled repayment in November 2016</td>
<td>1.68</td>
<td>2.67</td>
</tr>
<tr>
<td>Same-JLG Different-Religion Peers Missed Payment (Nov16)</td>
<td>The number of borrowers outside the borrower's religion in the JLG, excluding the borrower herself, who fail to pay the scheduled repayment in November 2016</td>
<td>0.20</td>
<td>0.83</td>
</tr>
<tr>
<td>Different-JLG Same-Religion Peers Missed Payment (Nov16)</td>
<td>The number of borrowers from the borrower's religion in the center, excluding the borrower's JLG, who fail to pay the scheduled repayment in November 2016</td>
<td>4.16</td>
<td>5.29</td>
</tr>
<tr>
<td>Different-JLG Different-Religion Peers Missed Payment (Nov16)</td>
<td>The number of borrowers outside the borrower's religion in the center, excluding the borrower's JLG, who fail to pay the scheduled repayment in November 2016</td>
<td>0.58</td>
<td>1.90</td>
</tr>
<tr>
<td>Missed Payment (Nov16)</td>
<td>Indicator set to 1 if the borrower fails to pay the scheduled repayment in November 2016</td>
<td>0.39</td>
<td>0.49</td>
</tr>
<tr>
<td>Center Missed Payment Rate (Pre Nov16)</td>
<td>The three-month average of the fraction of borrowers at the center who failed to pay the scheduled repayment in each of the months immediately preceding November 2016.</td>
<td>0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>Overdue Amount</td>
<td>The borrower's total overdue amount (in thousand Rupees) at the end of November 2016</td>
<td>0.03</td>
<td>0.35</td>
</tr>
<tr>
<td>Outstanding Principal</td>
<td>The borrower's outstanding principal (in thousand Rupees) at the end of November 2016</td>
<td>14.72</td>
<td>8.51</td>
</tr>
<tr>
<td>Brick House</td>
<td>Indicator set to 1 for the relatively less poor borrowers (i.e., those who live in brick houses rather than non-brick houses)</td>
<td>0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>Loan Amount</td>
<td>The borrower's loan amount (in thousand Rupees) at the time of demonetization</td>
<td>25</td>
<td>6.73</td>
</tr>
<tr>
<td>Age</td>
<td>Age (in years) of the borrower at the time of demonetization</td>
<td>36.9</td>
<td>8.85</td>
</tr>
<tr>
<td>Cycle</td>
<td>The borrower's loan cycle (i.e., the cumulative number of times the borrower has taken a loan from the firm)</td>
<td>1.5</td>
<td>0.91</td>
</tr>
<tr>
<td>Center Size</td>
<td>The number of borrowers in the center that the borrower belongs to</td>
<td>17.6</td>
<td>5.57</td>
</tr>
<tr>
<td>JLG Size</td>
<td>The number of borrowers in the joint liability group (JLG) that the borrower belongs to</td>
<td>5.64</td>
<td>3.34</td>
</tr>
<tr>
<td>Religion</td>
<td>Categorical variable for the borrower's religion (Hindu, Muslim, Sikh, or Christian)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Occupation</td>
<td>Categorical variable for the borrower's occupation (e.g., agriculture, retail)</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes. The sample is comprised of 1,982,862 unique borrowers with a loan that was active not only in November 2016 but also in at least December 2016. This allows analysis of the effect of peer missed payments in November 2016 on the borrower’s missed payments in subsequent months as is shown in Table 2.
### Table 2. Individual-Level Analysis of Loan Defaults

<table>
<thead>
<tr>
<th></th>
<th>(1) Missed Payment (Dec16-Feb17)</th>
<th>(2) Missed Payment (Dec16-Feb17)</th>
<th>(3) Missed Payment (Dec16-Feb17)</th>
<th>(4) Missed Payment (Dec16)</th>
<th>(5) Missed Payment (Dec16)</th>
<th>(6) Missed Payment (Dec16)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same-JLG Peers Missed Payment (Nov16)</td>
<td>0.01046 (0.00046)</td>
<td>0.00724 (0.00047)</td>
<td>0.01153 (0.00048)</td>
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<tr>
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<td>0.00478 (0.00041)</td>
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**Notes.** These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower’s missed payments in subsequent months. We use a dependent variable based on a three-month future duration, Missed Payment (Dec16-Feb17), in Columns 1-3, and a dependent variable based on a one-month future duration, Missed Payment (Dec16), in Columns 4-6. The sample for Columns 1-3 includes a small number of borrowers whose loan repayment obligations ended in Dec16 or Jan17; results are qualitatively unchanged if such borrowers are dropped. All regressions here rely on the borrower as a unit of analysis, and employ a linear probability model using the sample and variables described in Table 1. Standard errors, clustered at center level, are reported in parentheses.
Table 3. Further Analysis of Potential Peer Influence (Effect of Tie Strength Based on Having a Common Religion)

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<tr>
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<tr>
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<td>1,982,862</td>
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<td>0.494</td>
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<td>0.502</td>
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Notes. These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower’s missed payments in subsequent months, extending the analysis in Table 2 by now separately considering peers from same vs. different religions. As in Table 2, all regressions here rely on the borrower as a unit of analysis, and employ a linear probability model using the sample described in Table 1. Standard errors, clustered at center level, are reported in parentheses.
At the time of demonetization, the microfinance firm operated 536 branches across 15 states in India. The geography served by each branch was divided by the firm among an average of 5.7 loan officers. Each loan officer managed an area that covered a set of microfinance centers located in close proximity. Borrowers belonging to a center met periodically to make their scheduled repayments together. There were on average 15.5 borrowers per center, who were further divided into JLGs. Each JLG contained an average of 4.7 borrowers.

These plots show the average incidence of missed payments by month for the full sample of borrowers. Demonetization occurred on November 8, 2016. The x-axis labels denote the end of each respective month. The average monthly default rate in the pre-demonetization period was 1.64%.
Figure 3. Temporal Pattern of Full Collection Centers and Zero Collection Centers

Notes. “Full Collection Centers” refer to the centers where all borrowers made their scheduled repayment. “Zero Collection Centers” refer to the centers where no borrowers made their scheduled repayment. The plots show full collection centers and zero collection centers as a percentage of total centers. Demonetization occurred on November 8, 2016. The x-axis labels denote the end of each respective month.
Figure 4. Actual versus Simulated Distribution of Center-Level Missed Payment Rates

A
October 2016 (The Month before Demonetization)

B
November 2016 (The Month of Demonetization)

C
December 2016 (The Month after Demonetization)

Notes. These are kernel density distributions of actual versus simulated missed payments (10,000 permutations).
### SUPPLEMENTARY MATERIAL

#### Table S1. Heterogeneity across Centers: 100% Pre-Demonetization Repayment Centers versus Others

<table>
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<th>(2)</th>
<th>(3)</th>
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<tbody>
<tr>
<td></td>
<td>100% Repayment Center (PreNov16)</td>
<td>Not 100% Repayment Center (PreNov16)</td>
<td>All Centers</td>
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<td>Occupation Indicators</td>
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<td>Loan Officer Area FE</td>
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<td>R-squared</td>
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<td>0.490</td>
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**Notes.** These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower’s missed payments in subsequent months, extending the analysis in Table 2 by now analyzing the effect in 100% repayment centers (Pre Nov16) vs. other centers. As in Table 2, all regressions here rely on the borrower as a unit of analysis, and employ a linear probability model using the sample described in Table 1. Standard errors, clustered at center level, are reported in parentheses.
Table S2. Heterogeneity across Centers: New Centers versus Others

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<td>(Dec16-Feb17)</td>
<td>(Dec16-Feb17)</td>
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Notes. These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower’s missed payments in subsequent months, extending the analysis in Table 2 by now analyzing the effect in new centers (Pre Nov16) vs. other centers. As in Table 2, all regressions here rely on the borrower as a unit of analysis, and employ a linear probability model using the sample described in Table 1. Standard errors, clustered at center level, are reported in parentheses.
Figure S1. Missed Payment Rates for Borrowers Living in Brick vs. Non-Brick Houses

Notes. These plots show the average incidence of missed payments by month for the borrowers living in brick houses and non-brick houses. Demonetization occurred on November 8, 2016. The x-axis labels denote the end of each respective month. The average monthly default rate in the pre-demonetization period was 1.46% for borrowers living in brick houses and 1.74% for borrowers living in non-brick houses.
Figure S2. Frequency Distribution of Borrowers with Missed Payment

Actual: July 2016
Simulated: July 2016

Actual: August 2016
Simulated: August 2016

Actual: September 2016
Simulated: September 2016

Actual: October 2016
Simulated: October 2016
Notes. These plots depict the descriptive patterns in the distribution of missed payments.
Figure S3. Peer Influence Estimates by Categories of Number of Same-JLG Peers with Missed Payment and Different-JLG Peers with Missed Payment

Notes. These plots visually depict the results of a regression model that includes categorical indicator variables for different numbers of same-JLG and different-JLG peers with missed payment, rather than the respective continuous measures used in our main analyses. This analysis allows for the exploration of possible thresholds or other discontinuities in the relationship between the pattern of peer behavior and the likelihood of a borrower’s missed payment.