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Peer Influence and Microfinance Loan Defaults under Crisis Conditions: Evidence from Indian Demonetization

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The microfinance group lending model has been widely adopted as a strategy for financial inclusion. However, we argue that under crisis conditions where risk of individual loan defaults is already high, this approach contains a vulnerability: borrower-to-borrower connections within lending communities created to promote repayment can facilitate the spread of defaults. We test our arguments in the context of the liquidity crisis that followed India's 2016 demonetization policy. Using proprietary data on the repayment decisions of about two million microfinance borrowers, we document disproportionate localization of post-demonetization defaults within lending communities. We also find evidence consistent with borrower-to-borrower spread of defaults not only through formal joint liability connections, but through informal social connections, with the latter influence being stronger between borrowers from the same religion.

Keywords: Peer Influence; Group Lending; Microfinance; Loan Defaults; Demonetization

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1. INTRODUCTION

Firms commonly rely on social connections among external stakeholders to improve the efficiency and effectiveness of their operations (Dyer and Hatch, 2006; Gulati, Nohria, and Zaheer, 2000), particularly when operating in resource-poor environments (George et al., 2016; Jones Christensen et al., 2015; London and Hart, 2004; Luo and Kaul, 2019; Mair, Marti, and Ventresca, 2012). Perhaps the most prominent example is in microfinance (Ault and Spicer, 2014; Battilana and Dorado, 2010; Bruton et al., 2011; Cobb et al., 2016; Wry and Zhao, 2018), where the widespread "group lending" approach, which relies on social connections between borrowers who live in the same community (Haldar and Stiglitz, 2016), has fueled the growth of a large, global industry. Group lending today facilitates tens of millions of new loans every year, many in impoverished settings where alternative, conventional lending practices, such as the holding of collateral, are impracticable (Canales, 2014).[1]

A central feature of the group lending approach is the intentional development of social connections, between peer borrowers, to encourage and reinforce timely repayment. The most common group lending arrangement relies on both formal and informal borrower-to-borrower connections. Formal connections are achieved through 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: joint liability thus creates a system of "social collateral" characterized by borrowers' accountability not only to the lender, but also to each other (Besley and Coate, 1995). In addition, borrowers belong to larger lending centers, each composed of multiple joint

[1] The global microfinance industry originated approximately $157 billion in loans in 2020. As Buera et al. (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%). While our focus here is on group lending in the specific context of microfinance, variants of this approach are also found in other sectors targeting the base of the pyramid. Some examples include micronutrient supplements (Suchdev et al., 2010), agricultural products (Chen et al., 2013), water and sanitation products (Evans et al., 2014), and electricity (Schnitzer et al., 2014).

liability groups, in which the lending firm administers repayment and conducts a broader set of collective activities (such as experience sharing and oath-taking) that encourage timely repayment (Sanyal, 2009), and thus build *informal*, non-economic social connections and norms of repayment with peers with whom they do not share joint liability. This combination of formal and informal social connections has proven remarkably successful at achieving low loan default rates at low cost and has thus significantly expanded access to finance in emerging markets around the world (Banerjee, 2013; Canales and Greenberg, 2016).

While the group lending approach has produced remarkable performance overall, it has proven fragile in the face of external crises, several of which have led to mass defaults among group lending borrowers. For instance, widespread defaults have followed 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 (Guérin et al., 2015). Early models of group lending anticipated the possibility that defaults by jointly-liable peers might increase an individual borrower's repayment burden, and thus their cost of remaining in compliance (Besley and Coate, 1995), a mechanism that could plausibly lead to such unraveling. Yet empirical examinations of these crises have mostly focused on factors related to borrower profiles, such as the innate vulnerability of poor borrowers and the 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 and Stiglitz, 2016). By contrast, little empirical evidence exists regarding the role of joint liability itself in defaults under crisis conditions (Giné et al., 2011).

Even less is known about the role of informal, non-joint-liability social connections under crisis conditions. Previous research has linked informal social connections between borrowers to mass defaults in other contexts, such as mortgages (Gupta, 2019) and bank runs (Iyer and Puri, 2012). In these previously studied settings, however, such informal connections are unrelated to, or peripheral to, the firm's strategy. In group lending, by contrast, the cultivation of informal social connections between borrowers is a central and costly investment made in expectation of performance gains. In short, group lending is a setting in which the development of social connections is understood as *strategic* and central to organizational performance.

In this paper, we develop the argument that under crisis conditions, social connections developed between borrowers through firm activities can hasten the spread of loan defaults. In particular, we argue that the importance of social connections is not limited to formal joint liability; that is, informal social connections also play a significant role. We test these ideas empirically by analyzing the repayment behavior of approximately two million borrowers (all female) from a large for-profit Indian microfinance organization. On November 8, 2016, the Indian government voided (without advance notice) the legal status of all 500 and 1,000 rupee currency notes in circulation, effectively removing 87 percent of cash from the economy. This "demonetization" policy caused widespread economic disruption and distress in India's heavily cash-dependent economy (Chodorow-Reich et al., 2020; Natarajan, Mahmood, and Mitchell, 2019). Among the borrowers in our data, 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. The induced variation in missed payments across lending centers provides a natural opportunity to examine the link between peer influence and loan defaults during a crisis.[2]

Our data, which cover the four months before and the four months after the demonetization announcement, consist of monthly observations of the repayment status of approximately two

[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.

million borrowers belonging to 430 thousand joint liability groups, nested within 130 thousand lending centers. Our empirical approach identifies formal joint liability connections based on their membership within the same joint liability group. In addition, we identify informal, non-joint-liability social connections between peers based on their common membership in a single lending center—the unit within which lenders organize borrowers to regularly meet and connect with one another.

Our first set of analysis looks for evidence of the combined influence of these formal and informal connections on the distribution of loan defaults across centers. To do so, we implement a "shuffle test" approach that seeks to identify disproportionate localization of defaults within certain centers (Aral et al., 2009). Specifically, we compare the observed distribution of repayment rates across centers within a relatively small geographic area with a counterfactual scenario generated by randomly reassigning missed payments across all of the borrowers located within that small area. The results of this shuffle test indicate that loan default behavior was indeed significantly more localized within centers than would be expected in the absence of social influence between peers. Following the inferential strategy of prior research (Alcácer and Zhao, 2016), we take this as indirect evidence of the presence of localized peer influence within these centers.

Our second, complementary set of analysis uses regression models to estimate the influence of an individual borrower's peers on her repayment behavior following demonetization. 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. We further consider how these two types of peer influence differ for peers who belong to the same versus different religion as the focal borrower—a strong proxy for non-economic social solidarity in this context (Munshi and Myaux, 2006)—and find that shared religion strongly increases the influence of non-joint-liability peers.

Overall, our research presents evidence consistent with an important role for peer influence in the spread of loan defaults under crisis conditions, a finding with broader implications for the strategic consequences of such social connections. Importantly, we find evidence that this peer influence is associated with not only the formal joint liability relationships emphasized by the group lending literature but also the broader informal social connections between borrowers co-located within the same lending center. We further show that this influence is enhanced for social connections associated with factors unrelated to group lending, such as membership in the same religious group. Taken together, our findings reinforce the importance of considering environmental contingencies when formulating strategies that rely on social connections among stakeholders, particularly in the context of emerging markets where crises are, unfortunately, relatively commonplace.

2. GROUP LENDING, PEER INFLUENCE AND LOAN DEFAULTS UNDER CRISIS CONDITIONS

Group lending refers to the formation and cultivation of persistent, localized communities of individual borrowers in the course of loan disbursement and administration, especially in the context of microfinance (Besley and Coate, 1995). Group lending is an alternative to traditional individual loans, in which a borrower's economic incentives to repay are based on the threat of penalties that would be incurred following the lender's enforcement of the loan contract. By relying on a borrower's peers to encourage timely repayment, group lending overcomes limitations faced by firms that seek to serve low-income customers in emerging market contexts, where institutions for contract enforcement can be weak and borrowers tend to lack adequate collateral or credit history to support traditional, individual lending (Khanna, 2018).

2.1. Formal vs. Informal Peer Influence in Group Lending

In the typical group lending arrangement, each borrower belongs to a single formal joint liability group (JLG). Lenders form "centers" by aggregating multiple joint liability groups (JLGs). At the center level, a representative from the firm (typically called a "loan officer") organizes regular meetings for borrowers belonging to a center. These center meetings have two primary goals: first, to efficiently collect loan payments from borrowers located in the same geographic area and second, to strengthen the informal social connections that support timely repayment. Center meetings therefore include activities that reinforce norms of personal support (Sanyal 2009, 2015), financial stewardship and mutual accountability (Banerjee and Duflo, 2011; Bu and Liao, 2021; Feigenberg et al., 2013; Khanna, 2018).[3] Participation in group lending thus leads borrowers to develop not only formal "joint-liability" connections to peers belonging to the same JLG, but also informal "non-joint-liability" connections with other borrowers with whom they are geographically co-located and socially connected, but share no financial liability.

A substantial literature in development economics explains how group lending limits borrower defaults, mostly focusing on the role of joint liability contracts, which produce an incentive structure that may decrease rates of default through mechanisms that include peer

[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 et al., 2016).

screening of borrowers and monitoring of post-loan effort to repay (Armendáriz and Morduch, 2010; Roodman, 2012; Stiglitz, 1990). The most relevant mechanism to our analysis relates to the model developed by Besley and Coate (1995), who propose joint liability creates strong incentives for borrowers to repay, as default would incur strong social sanctions from joint liability partners.

A smaller, more recent literature suggests that informal, non-joint-liability connections may perform similar functions (de Quidt et al., 2016). This research finds some evidence that high repayment rates can be achieved even in the absence of 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 repayment behavior at least in their context seemed to be driven primarily by informal and not formal relationships (see also Attanasio et al., 2015).

2.2. The Role of Formal (Joint Liability) Peer Connections under Crisis Conditions

Despite the consistently low default rates achieved by group lending under normal conditions (Banerjee, 2013; Cassar et al., 2007; Karlan, 2007), spikes in defaults have been observed during natural, economic or political crises, sometimes even leading to complete breakdowns of lending operations (Guérin et al., 2015). Empirical development economics research has exploited these failures to study questions unrelated to peer influence, such as the estimation of welfare effects of microfinance (e.g., Breza and Kinnan, 2021). But limited empirical evidence exists regarding the role of social connections in the spread of crisis-induced defaulting behavior in the first place, even among peers connected via joint liability (Giné et al., 2011). Therefore, before turning to the role of *informal* (non-joint-liability) peer connections among borrowers, we first formulate our baseline hypothesis regarding how this *formal* (within-JLG) social influence between jointly-liable borrowers can be expected to affect defaulting behavior under crisis conditions.

Theoretical models of joint liability note that if a borrower's peers default, her own cost of repayment increases, thus making repayment less attractive and increasing the likelihood that she herself will default (Besley and Coate, 1995). Under normal conditions, if defaults are rare, this mechanism should have minimal influence. However, when an external crisis leads to a short-term spike in defaults, the spillover effects of these defaults on the peers who share joint liability with the defaulting borrowers may be substantial. We can summarize the above argument in the form of a first (baseline) hypothesis that a greater extent of loan default among joint liability peers will thus lead to an increase in the focal borrower's subsequent likelihood of default:

Hypothesis 1 *(H1). [Baseline] A borrower will be more likely to default on her loan following more defaults by peers with whom she shares a formal (joint liability) relationship.*

2.3. The Role of Informal (Non-Joint-Liability) Peer Connections under Crisis Conditions

With regard to informal, non-joint-liability connections in group lending, the empirical microfinance literature offers few predictions for their importance under crisis conditions. However, a growing body of research from settings outside of microfinance 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. 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 et al., 2016). Gupta (2019) studies the mortgage loans market during the 2008 financial crisis, and finds evidence that contagion of defaults among geographically proximal borrowers was driven by the spread of information related to lender enforcement and the stigma associated with default.

Drawing from the above studies examining loan defaults in contexts beyond microfinance, we also suggest that, in addition to the direct economic channel through which jointly liable peers' defaults change an individual borrower's repayment decision in microfinance lending, non-joint-liability peers' defaults can also make it more likely for a borrower to default. Our arguments focus on the availability of information about peer defaults and the resulting change in expectations about the sanctions that would follow a borrower's choice to default. Previous research across fields has suggested that individuals rely heavily on social information in formulating their actions, particularly under crisis conditions in which 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 (e.g., 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 for making 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 information-based arguments suggest a likely possibility of the diffusion of defaults via social relationships: peers' defaults are likely to convey information about those peers' beliefs regarding penalties that govern repayment, which include enforcement actions by the lending firm and social penalties (or withdrawal of support) from other borrowers. When peers make timely repayment, their behavior signals to a borrower that the expected costs of repayment do not exceed the expected penalties of default, both from peers and from the lending firm (Guiso et al., 2013), and that peers expect to continue pressuring and supporting one another towards making timely repayments. Peer defaults, by contrast, signal the expectation that the overall penalties from the parties to whom they are accountable—the lending firm and other peers—are reduced. That is, in the uncertainty surrounding a crisis, we argue that peer defaults 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. Importantly, this informational mechanism does not require joint liability, and is therefore relevant even for informal, non-joint-liability social connections.

Based on these arguments, we propose that a borrower will be more likely to default on her loan when other informally connected borrowers from her local community have also recently defaulted:

Hypothesis 2 *(H2). A borrower will be more likely to default on her loan following more defaults by peers with whom she shares an informal (center co-membership without joint liability) relationship.*

2.4. Common Religion as a Moderator

Thus far, we have argued that default by a greater number of peers, of both joint-liability and non-joint-liability types, is likely to increase a borrower's own likelihood of subsequent default. We now extend this argument to suggest that the influence of both types of peers is strongest for the subset of peers with whom the borrower is connected through non-economic social ties that are exogenous to the practice of group lending. In the absence of direct observation of the nature and strength of a borrower's social ties with specific peers, an alternate approach involves inferring the presence of such ties indirectly through an appropriate proxy. We therefore focus on the presence of a common religion between the borrowers and their peers as a proxy for a stronger social tie. We hypothesize that shared religion between borrowers strengthens the social influence that arises from their joint-liability and non-joint-liability connections.

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 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 and Bagde, 2015; Reagans, 2011) and economics (Alesina and Ferrara, 2005; Easterly and 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.

In many societies, including India, religion is a primary social dimension of social group membership. While religion is an important dimension of social distinction 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 et al., 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.

Based on the above arguments, we expect that a borrower's likelihood of subsequent default will be more sensitive to the behavior of her peers that belong to the same religion versus those who do not. We further expect this moderating effect to apply to both joint-liability and non-joint-liability relationships, and therefore list the two cases separately to clarify the presentation of analysis and evidence related to each later in the paper:

Hypothesis 3a *(H3a). The strength of the effect of jointly-liable peers' defaults on a borrower's likelihood of subsequent default (as hypothesized in H1) will be stronger for the peers that share the borrower's religion than for those that do not.*

Hypothesis 3b *(H3b). The strength of the effect of non-jointly-liable peers' defaults on a borrower's likelihood of subsequent default (as hypothesized in H2) will be stronger for the peers that share the borrower's religion than for those that do not.*

3. RESEARCH SETTING, DATA AND EMPIRICAL APPROACH

3.1 India's 2016 Demonetization Policy

At 8pm on the evening of 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).[4] The policy was announced via a surprise address televised simultaneously nationwide, and the policy (henceforth referred to as "demonetization") went into effect at

[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).

midnight the same day (Natarajan et al., 2019). Although the government also announced that the affected currency notes could be exchanged for new and valid currency notes at formal financial institutions, the exchange was in practice severely limited by delays in the printing and distribution of new bills as well as daily per-person exchange limits. The policy therefore ended up dramatically (even if temporarily) reducing the liquid assets of a large majority of the Indian households (Banerjee et al., 2019; Chakravorti, 2017).

In addition to widespread media anecdotes, empirical research has also documented that demonetization had a broad and immediate impact 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). These effects appear to have been particularly acute among the rural poor, who were most dependent on cash-based rather than digital transactions. As one expert put it, "*Liquidity has been sucked out. You have stopped market transactions for 70 percent of the economy. The poor will suffer more.*" (Sanyal, 2018: 39). Several features of the microfinance industry, in particular, made it especially vulnerable to disruption following demonetization. Microfinance borrowers are relatively poor and operate in informal sectors that rely heavily on physical currency (Collins et al., 2009); in addition, a borrower's choice to access microfinance loans generally indicates a lack of overall liquidity.

3.2 Borrower-Level Data from a Microfinance Firm

Our study relies on proprietary, borrower-level repayments data obtained from a large Indian microfinance firm (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 states in India, and lent exclusively to individuals identifying as women.[5] Our dataset covers the 2,036,108 borrowers who had active loans with the microfinance 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.

The microfinance firm's organization, borrower demographics, and group lending procedures were typical in the microfinance industry. An assigned loan officer collected repayments at lending center meetings. A mandatory condition for a borrower being considered compliant was her regular attendance at center-level meetings, which 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 the microfinance sector (e.g., Canales, 2014), loan terms were highly standardized: nearly all borrowers received initial loans of 25,000 rupees (approximately $375), to be repaid in regular installments, due once every two weeks over a duration of two years. No collateral was expected, consistent with typical practice in group lending. Upon repayment of their loan balance, borrowers with strong repayment 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 et al., 2013; Bulte et al., 2017; Canales, 2014; Karlan and Zinman, 2011).

[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).

In order to comply with Indian regulatory requirements for microfinance institutions, only individuals with a monthly household income of 12,000 rupees ($180) 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. Religious membership was consistent with overall population statistics for the regions where the firm operated. 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 slightly 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.

[Insert Figure 1 here]

Borrowers within a center were further divided into smaller "joint liability groups" (JLGs) (average size: 4.7 borrowers). Borrowers were only legally liable for repayment of loans held by peers in their joint liability group, but these boundaries were 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 reinforce social capital and "solidarity" among borrowers within a center

(Khanna, 2018: 108).[7] Interviews with loan officers and borrowers themselves confirmed that all activities were conducted at the center-level, and that JLG boundaries were rarely acknowledged. 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 condition. We shall neither accept nor offer any commission to center members, staff, and others."

3.3. Empirical Approach for Examining Peer Influence within Lending Centers

We now explain our empirical approach for examining how both formal and informal peer influence might have influenced loan repayment behavior under crisis conditions. Following prior management research that also examines loan repayment in the context of microfinance (Canales and Greenberg, 2016; Doering, 2018), we define *Missed Payment* as a binary variable equal to one if a borrower failed to make a scheduled payment in a given month, and zero otherwise.

In terms of summary statistics, as expected, the overall rate of missed payment rate in our data 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

[7] 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.

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).[8]

[Insert Figure 2 here]

We conduct two complementary sets of empirical analysis to evaluate the possible presence of peer influence shaping the observed pattern of loan defaults under crisis conditions. The first examines center-level differences in the average rate of missed payment, and tests the possibility of clustering of missed payments within socially connected 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 for the presence of social influence among co-located economic actors (Jaffe et al., 1993; Alcácer and Zhao, 2016). Following a similar logic, we examine the degree of clustering of missed loan payments within lending centers as indirect, indicative evidence of localized social influence among borrowers belonging to the same center.[9] Our second set of analysis complements the first by using individual-level regression models to estimate peer influence affecting repayments at the individual borrower level. Specifically, we estimate the extent to which the loan repayment behavior of peers in the month of demonetization (November 2016) affects a borrower's likelihood of default in subsequent months. These analyses focus in particular on how the incidence of missed payment for the focal

[8] 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 et al., 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.

[9] 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 et al., 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 based on an exogenous driver of this strength, namely, having a shared religion.

borrower is driven by the previous missed payments of joint-liability and non-joint-liability peers.[10]

Given the wide geographic diversity across centers in our sample, a central challenge in both analyses mentioned above 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 and Greenberg, 2016). Because we are unable to observe all such factors directly, we instead use statistical means to account for, to as great a degree as 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 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 significantly mitigate concerns related to geography-related unobserved heterogeneity.

[10] Because we are constrained by our data being monthly, we are unable to test relational influence within a given month. Given this constraint, our peer influence analyses focus on month as the temporal unit of analysis.

4. CENTER-LEVEL ANALYSIS OF CLUSTERING OF LOAN DEFAULTS

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, as previously described (see Figure 2). If within-center social influence were an important contributor to this jump, we would expect it to have magnified differences in the incidence of default across centers. That is, social influence should lead to a greater clustering of defaults within certain centers than would otherwise be observed.

A simple but coarse indicator of this center-level clustering is the appearance of either 100% repayment 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 per cent. This jump is suggestive of localized social influence, post-demonetization, in borrower decisions to default. However, a more refined test of clustering requires a more granular measure of clustering, as well as a more appropriate counterfactual to compare the observed patterns against.

[Insert Figure 3 here]

We implement such improvements by comparing the observed clustering of defaults with a simulated, counterfactual scenario generated by reassigning actual outcomes (i.e., borrower default decisions) across individuals, a strategy sometimes called the "shuffle test" (Alcácer and Zhao, 2016; Aral et al., 2009; Christakis and Fowler, 2007). In this approach, a special form of "placebo" test (Athey and Imbens, 2017), we reassign defaults through a random process with the same likelihood of default but independent of social connections, thus generating a counterfactual with which the clustering of actual default behavior can be compared. 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 and Glaeser, 1997) or knowledge spillovers (Jaffe et al., 1993).

A key feature of our implementation is that we reassign individual borrower defaults across borrowers belonging to any of the lending centers that lie within the same loan officer area (while keeping the total number of defaults in any given loan officer area the same as in the original data). 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 few square kilometers.[11] Conducting a separate "shuffle" for each loan officer area helps address possible concerns that unobserved heterogeneity across loan officers themselves, as well as in the geographic and economic conditions in their respective coverage areas, might also affect loan defaults.[12] It is worth noting that the counterfactual generated by randomly reassigning missed payments among borrowers within each 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 across the centers within the loan officer area. 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.[13]

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[11] 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.
[12] We should acknowledge that this research design does not allow us to account for any differences that might exist even between centers belonging to the same loan officer area, as we are constrained by the limitations of our data.
[13] While variation in results across multiple permutations was limited, we conducted 10,000 permutations to ensure a stable distribution.

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 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.[14]

[Insert Figure 4 here]

To summarize, our center-level analysis indicates that increased missed payments post-demonetization are disproportionately clustered within some centers. Further, since our shuffle test only compares centers in close geographic proximity and served by a single loan officer, this clustering is unlikely to be driven by loan officer or geography-specific differences, and hence seems likely to be driven by peer influence operating at the center level. Nonetheless, although the shuffle test provides useful insight into clustering of defaults, it cannot directly estimate the peer influence among specific borrowers, nor can it distinguish between the role of formal (joint-liability) connections and informal (non-joint-liability) connections. To make further progress on these dimensions, we now turn to fine-grained individual-level analysis.

[14] 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.

5. INDIVIDUAL-LEVEL ANALYSIS OF LOAN DEFAULTS

In this section, we formally test our three hypotheses regarding peer influence through analysis of default decisions by individual borrowers. Specifically, we estimate a borrower's choice to default in post-demonetization months (December 2016-February 2017) as influenced by the default decisions by her peers (to whom she is either formally or informally connected) in the month of demonetization (November 2016). Our analysis consists of two main steps: (i) estimating separately peer influence in formal, joint-liability (H1) and informal, non-joint-liability (H2) relationships; (ii) estimating the degree to which stronger non-economic ties (using religious commonality as a proxy for tie strength) magnifies these effects (H3a and H3b).

5.1. The Role of Formal and Informal Peer Influence under Crisis Conditions

We estimate individual-level regression models that predict loan defaults at the borrower level, the smallest unit at which we can observe peer influence dynamics. 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.[15] Importantly, all models include as 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 robust standard errors clustered

[15] 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 et al., 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 et al., 2011) and neighborhood bankruptcies (Agarwal et al., 2020). Our regression analysis most closely follows the linear social interaction models recommended by Blume et al. (2015).

at the center level. The formal regression equation, which employs a linear probability model to minimize functional form dependency, is as follows:[16]

$$Missed\ Payment\ (Dec16\text{-}Feb17)_i = \alpha + \beta_1 Same\text{-}JLG\ Peers\ Missed\ Payment\ (Nov16)_i + \beta_x X_i + \gamma_{Loan\ Officer\ Area\ (i)} + \varepsilon_i \quad (1)$$

The estimator β_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 the regression specification is the inclusion of loan officer area fixed effects, $\gamma_{Loan\ Officer\ Area\ (i)}$, to control for unobserved heterogeneity across loan officer areas that might drive month-to-month default rates (Angst et al., 2010), including idiosyncratic differences across the loan officers themselves (Canales and Greenberg, 2016; Doering, 2018). Table 1 provides definitions and summary statistics for all of the 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 (β = 0.0105, 95% CI [0.0096, 0.0114], p = 0.000). This is consistent with Hypothesis 1, which predicted that borrowers will be more likely to miss payments when other borrowers in their joint liability group had previously missed a payment.

[Insert Table 2 here]

[16] 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 and 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.

Turning to Hypothesis 2, 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 regression 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], $p = 0.000$). The finding is consistent with Hypothesis 2, which predicted that a borrower will be more likely to miss payments when more of her non-joint-liability peers had previously missed a payment.

Our preferred regression specification for both Hypotheses 1 and 2 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 of the 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 find results qualitatively similar to Columns 1-3. In the full specification (Column 6), the estimated magnitude of the social 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, $p = 0.039$).[17]

5.2. Common Religion as a Moderator

We now turn to Hypotheses 3a and 3b, which predicts that the peer influences described above ought to be stronger for formal as well as informal peers belonging to the same religion as the focal borrower. To test these hypotheses, we refine the 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.

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.

[17] 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.

Taken together, we find strong support for Hypothesis 3b, but not for Hypothesis 3a. In other words, membership in the same religious group (an exogenous non-economic measure of the strength of social connection) significantly moderates peer influence via informal, non-joint-liability connections (H3b) but not via formal, joint-liability connections (H3a). This difference is consistent with the idea that the mechanism underlying peer influence for joint-liability connections is primarily based on economic factors (i.e., the increase in liability resulting from their peers' defaults), whereas peer influence for non-joint-liability connection is based to a greater degree on informal social sanctions among peers. The latter, informal mechanism therefore appears to be more contingent on the strength of the social relationship among peers that exists outside of group lending activities. This conclusion also remains unchanged based on examination of our alternate dependent variable in Column 6.

[Insert Table 3 here]

6. EXPLORATORY ANALYSIS OF CROSS-CENTER HETEROGENEITY

In this section, we report on further analyses that shed light on factors driving the observed loan default patterns, especially focusing on possible cross-center differences in peer influence.

6.1. Differences in Pre-Demonetization Repayment Rates across Centers

In line with a 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 and Stiglitz, 2016), we considered whether the effect of peer influence might be moderated 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 to test Hypotheses 1 and 2 earlier, 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 peer influence among borrowers was indeed stronger in centers with perfect repayment rates pre-demonetization, evidence consistent with the presence of persistent center-level norms.[18]

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 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 that tested Hypotheses 1 and 2, this time distinguishing borrowers from new versus old centers. The findings, reported in detail in Table S2 in the 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.[19] This

[18] 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.
[19] 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, *Same-JLG Peers Missed Payment (Nov16)* × *New Center* and *Different-JLG Peers Missed Payment (Nov16)* × *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.

pattern suggests that even firm-facilitated interactions with peers that were initiated relatively recently—whether through formal joint liability or informal social interaction—were sufficient to produce peer effects in crisis.

7. DISCUSSION AND CONCLUSION

In this paper, we have examined the role of local social connections among microfinance borrowers in the spread of missed payments under crisis conditions. We argue that missed payments might spread not only through formal connections among borrowers in the same joint liability group, but also through informal connections more generally among borrowers who belong to the same lending center. Analysis of individual-level repayment patterns by clients of a microfinance firm following India's 2016 demonetization policy supports these arguments by showing that defaults by not only her joint liability connections but also non-joint-liability connections is an important predictor of a borrower's propensity to subsequently default. Our research thus contributes to the broader management literature that seeks to understand how adverse behaviors may spread among a firm's stakeholders who are socially connected (Chan et al., 2021; Greve et al., 2016; Gupta, 2019), particularly when these connections serve a specific strategic purpose. While much work has emphasized the strategic benefits to firms of building social capital (Adler and Kwon, 2002) and trust (Burt, 2011) among their stakeholders, our findings join an increasing recognition of the potential "dark side of embeddedness" (Sorenson and Waguespack, 2006).

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 and Malmendier, 2013) or geographic variation (Hong, Kubik, and Stein 2005)."[20] 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 and Puri, 2012). Our context, by contrast, directly identifies those peer relationships that have been cultivated 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.[21] Research on social networks generally views peer influence as a function of the structural patterns of external events and relationships between individuals, often overlooking differences in the motivations of particular individuals. Our study extends this work by arguing and showing that religious similarity amplifies their susceptibility to peer influence. 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, and Zou, 2021).

Finally, our work contributes specifically to management research related to group lending and microfinance. This growing area of research has generally focused on organization-level strategies, examining how differences in the business environment affect outcomes including pro-social outreach (Wry and Zhao, 2018; Zhao and Wry, 2016), transaction costs and operating models (Ault, 2016; Ault and Spicer, 2014; Garmaise and Natividad, 2010), and resource acquisition (Cobb et al., 2016; Zhao and Lounsbury, 2016). A smaller set of studies has emphasized differences in the dyadic relationships between loan officers and borrowers as a key

[20] A few notable exceptions exist, e.g., see Hasan and Bagde (2015) in organizations research and Feigenberg et al. (2013) in the development literature. Both studies leverage the exogenous assignment of actors to peer groups.

[21] An important feature of our context is that all borrowers were women. While it is common for microfinance firms to lend exclusively to women, our findings should be interpreted in this context. Whether the strength of peer influence is associated with variation in a borrower's (and peers) gender is an important question for future research.

factor influencing lending outcomes (Canales, 2014; Canales and Greenberg, 2016; Doering 2018). We add to the latter, individual-level work by highlighting the importance and consequences of relationships *between borrowers*, both economic and non-economic in nature, under crisis conditions.

As in most empirical studies, the external generalizability of our findings is limited by features of our specific empirical context. The borrowers in our data are numerous and representative of poor women in India, and 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 types of 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 firm, or for the society at large, of relying on social connections in its business model. Further, while defaults generally negatively affect the lending firm's commercial performance, defaults should not be assumed to have negative consequences when taking borrower well-being into account. 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.

Our reliance on proprietary, internal repayments data comes with its own limitations. 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-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 comparison 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 strategic reliance on social connections between stakeholders, a tactic shown to be of particular importance for reaching the global poor (London and Hart, 2004). 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.

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Table 1. Definition of Variables for Individual-Level Analysis of Peer Influence

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

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 Peer Influence in Loan Defaults (H1, H2)

	(1) *Missed Payment (Dec16-Feb17)*	(2) *Missed Payment (Dec16-Feb17)*	(3) *Missed Payment (Dec16-Feb17)*	(4) *Missed Payment (Dec16)*	(5) *Missed Payment (Dec16)*	(6) *Missed Payment (Dec16)*
Same-JLG Peers Missed Payment (Nov16)	0.01046		0.00724	0.01153		0.00820
	(0.00046)		(0.00047)	(0.00048)		(0.00050)
Different-JLG Peers Missed Payment (Nov16)		0.00766	0.00666		0.00802	0.00689
		(0.00020)	(0.00022)		(0.00021)	(0.00023)
Missed Payment (Nov16)	0.29999	0.28239	0.26900	0.34447	0.32757	0.31239
	(0.00159)	(0.00142)	(0.00133)	(0.00169)	(0.00151)	(0.00142)
Center Missed Payment Rate (PreNov16)	0.21147	0.19926	0.19160	0.22332	0.21142	0.20275
	(0.00962)	(0.00924)	(0.00935)	(0.00985)	(0.00948)	(0.00960)
Overdue Amount	0.01661	0.01722	0.01827	0.02437	0.02490	0.02609
	(0.00122)	(0.00123)	(0.00124)	(0.00134)	(0.00135)	(0.00137)
Outstanding Principal	0.00073	0.00083	0.00080	0.00082	0.00093	0.00089
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Brick House	-0.00265	-0.00271	-0.00290	-0.00292	-0.00296	-0.00317
	(0.00136)	(0.00136)	(0.00136)	(0.00135)	(0.00135)	(0.00134)
Loan Amount	0.00048	0.00048	0.00051	-0.00048	-0.00048	-0.00044
	(0.00014)	(0.00014)	(0.00014)	(0.00013)	(0.00013)	(0.00013)
Age	-0.00064	-0.00063	-0.00063	-0.00056	-0.00056	-0.00056
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Cycle	0.00571	0.00565	0.00559	0.01118	0.01112	0.01105
	(0.00072)	(0.00072)	(0.00072)	(0.00072)	(0.00072)	(0.00072)
Center Size	0.00134	-0.00183	-0.00148	0.00117	-0.00215	-0.00175
	(0.00015)	(0.00018)	(0.00019)	(0.00015)	(0.00018)	(0.00018)
JLG Size	-0.00238	0.00467	0.00146	-0.00283	0.00478	0.00114
	(0.00046)	(0.00041)	(0.00050)	(0.00046)	(0.00041)	(0.00049)
Religion Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,982,862	1,982,862	1,982,862	1,982,862	1,982,862	1,982,862
R-squared	0.492	0.493	0.494	0.500	0.501	0.502

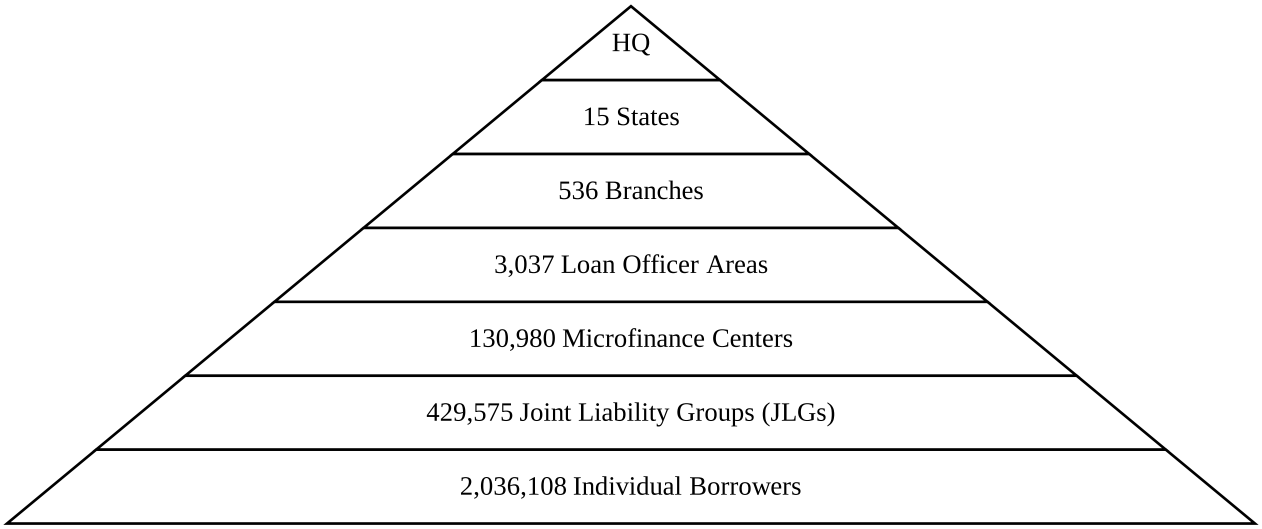
Notes. These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower's missed payments in subsequent months. We use a dependent variable based on a three-month future duration, *Missed Payment (Dec16-Feb17),* 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. The Moderating Effect of Tie Strength Based on Having a Common Religion (H3a, H3b)

	(1) *Missed Payment (Dec16-Feb17)*	(2) *Missed Payment (Dec16-Feb17)*	(3) *Missed Payment (Dec16-Feb17)*	(4) *Missed Payment (Dec16)*	(5) *Missed Payment (Dec16)*	(6) *Missed Payment (Dec16)*
Same-JLG Same-Religion Peers Missed Payment (Nov16)	0.01051		0.00717	0.01160		0.00813
	(0.00047)		(0.00048)	(0.00049)		(0.00051)
Same-JLG Different-Religion Peers Missed Payment (Nov16)	0.00995		0.00789	0.01088		0.00882
	(0.00071)		(0.00077)	(0.00075)		(0.00081)
Different-JLG Same-Religion Peers Missed Payment (Nov16)		0.00782	0.00684		0.00820	0.00709
		(0.00021)	(0.00023)		(0.00022)	(0.00024)
Different-JLG Different-Religion Peers Missed Payment (Nov16)		0.00648	0.00536		0.00673	0.00549
		(0.00032)	(0.00035)		(0.00034)	(0.00037)
Missed Payment (Nov16)	0.29998	0.28224	0.26886	0.34446	0.32741	0.31224
	(0.00159)	(0.00142)	(0.00133)	(0.00169)	(0.00151)	(0.00142)
Center Missed Payment Rate (PreNov16)	0.21149	0.19930	0.19164	0.22334	0.21147	0.20279
	(0.00962)	(0.00924)	(0.00936)	(0.00986)	(0.00948)	(0.00960)
Overdue Amount	0.01660	0.01724	0.01828	0.02437	0.02492	0.02611
	(0.00122)	(0.00123)	(0.00124)	(0.00134)	(0.00135)	(0.00137)
Outstanding Principal	0.00073	0.00083	0.00080	0.00082	0.00093	0.00089
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Brick House	-0.00265	-0.00270	-0.00289	-0.00292	-0.00295	-0.00316
	(0.00136)	(0.00136)	(0.00136)	(0.00135)	(0.00135)	(0.00134)
Loan Amount	0.00048	0.00048	0.00052	-0.00048	-0.00048	-0.00044
	(0.00014)	(0.00014)	(0.00014)	(0.00013)	(0.00013)	(0.00013)
Age	-0.00064	-0.00063	-0.00063	-0.00056	-0.00056	-0.00056
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Cycle	0.00572	0.00564	0.00558	0.01118	0.01111	0.01103
	(0.00072)	(0.00072)	(0.00072)	(0.00072)	(0.00072)	(0.00072)
Center Size	0.00134	-0.00183	-0.00147	0.00117	-0.00214	-0.00174
	(0.00015)	(0.00018)	(0.00019)	(0.00015)	(0.00018)	(0.00018)
JLG Size	-0.00238	0.00467	0.00145	-0.00283	0.00478	0.00114
	(0.00046)	(0.00041)	(0.00050)	(0.00046)	(0.00041)	(0.00049)
Religion Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,982,862	1,982,862	1,982,862	1,982,862	1,982,862	1,982,862
R-squared	0.492	0.493	0.494	0.500	0.501	0.502

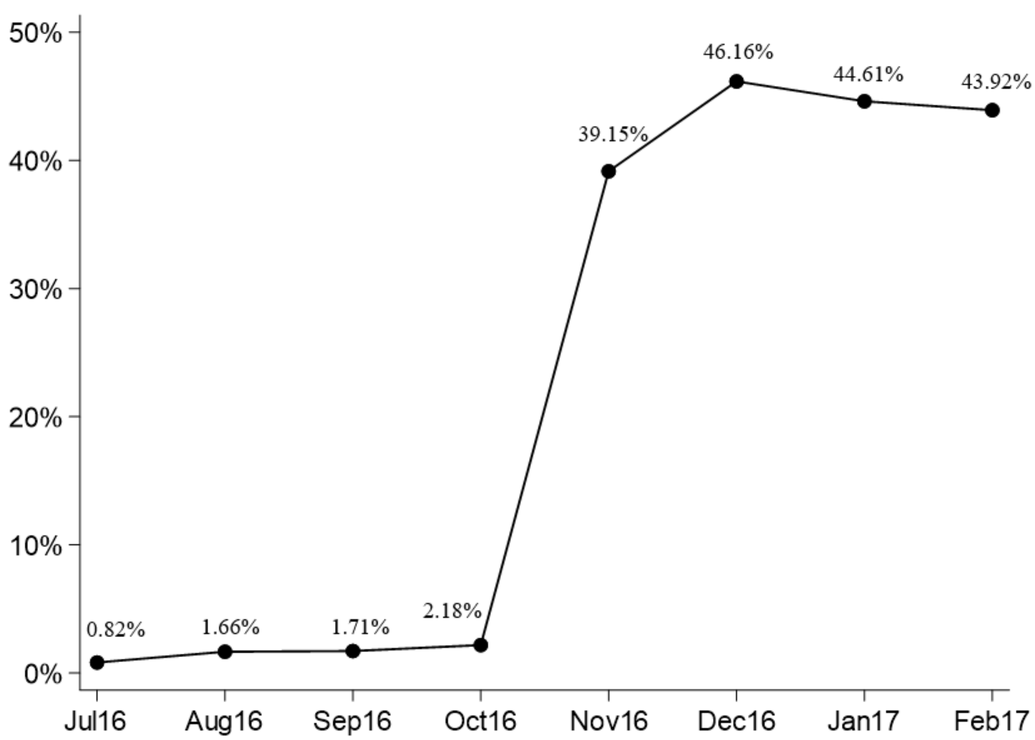
Notes. These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower's missed payments in subsequent months, extending the analysis in Table 2 by now separately considering peers from same vs. different religion. 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 1. Organization Structure of the Microfinance Firm



Notes. 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.

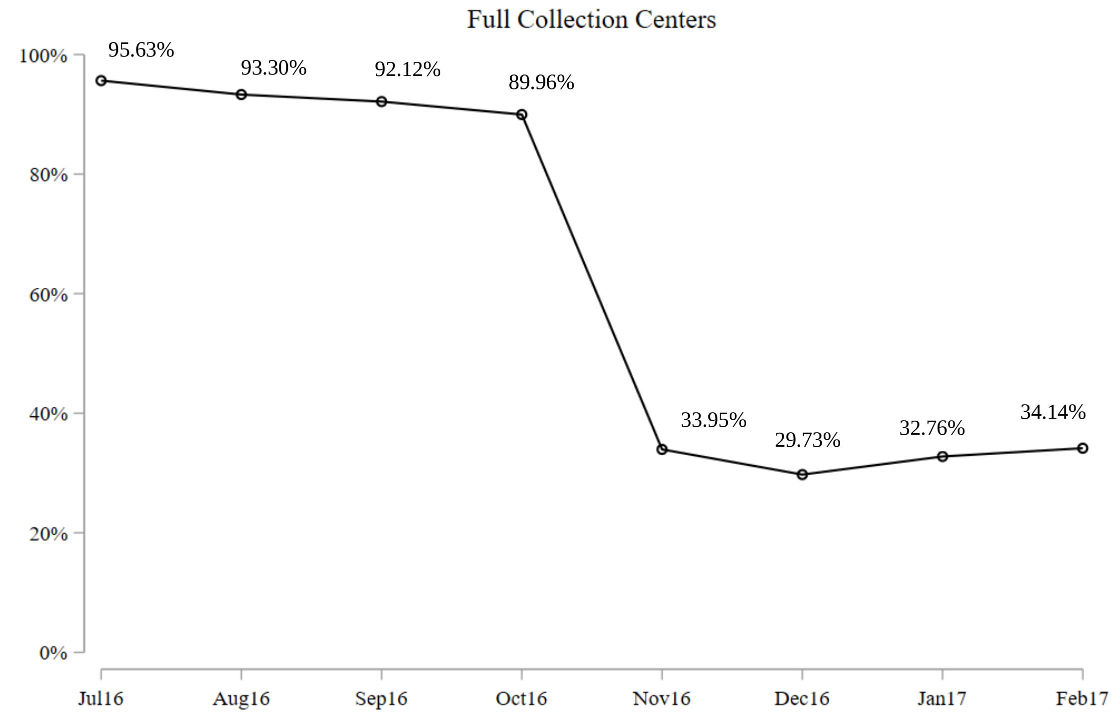
Figure 2. Temporal Pattern of Monthly Missed Payment Rates



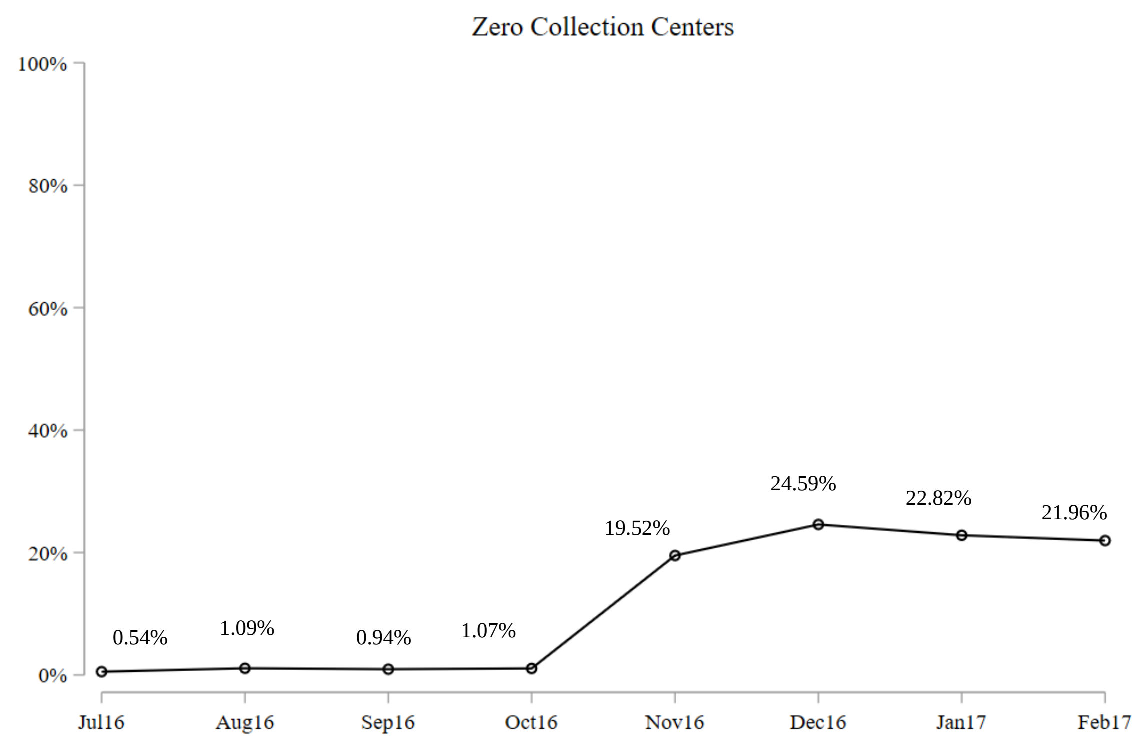
Notes. These plots show the average incidence of missed payments by month for the full sample of borrowers. Demonetization occurred on November 8, 2016. The x-axis labels denote the end of each respective month. The average monthly default rate in the pre-demonetization period was 1.64%.

Figure 3. Temporal Pattern of Full Collection Centers and Zero Collection Centers

A

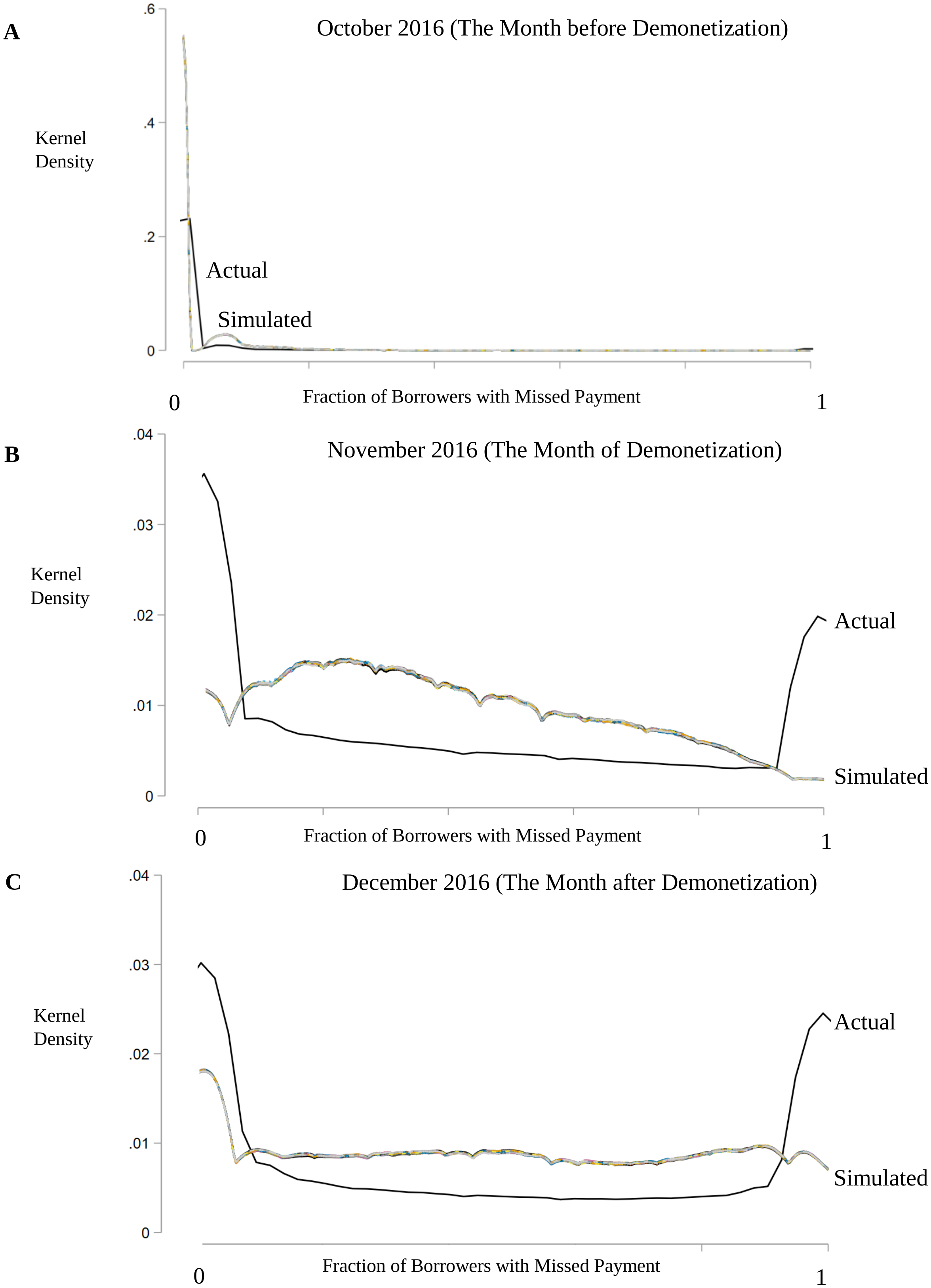


B



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



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

SUPPLEMENTARY MATERIAL

Table S1. Heterogeneity across Centers in the Strength of Peers Influence in 100% Pre-Demonetization Repayment Centers versus Other Centers

	(1)	(2)	(3)
	100% Repayment Center (PreNov16)	Not 100% Repayment Center (PreNov16)	All Centers
	Missed Payment (Dec16-Feb17)	*Missed Payment (Dec16-Feb17)*	*Missed Payment (Dec16-Feb17)*
Same-JLG Peers Missed Payment (Nov16)			
× 100% Repayment Center (PreNov16)			0.00753
			(0.00061)
Different-JLG Peers Missed Payment (Nov16)			
× 100% Repayment Center (PreNov16)			0.00405
			(0.00032)
Missed Payment (Nov16)			
× 100% Repayment Center (PreNov16)			-0.03754
			(0.00376)
100% Repayment Center (PreNov16)			-0.08233
			(0.00403)
Same-JLG Peers Missed Payment (Nov16)	0.00793	0.00350	0.00081
	(0.00052)	(0.00115)	(0.00064)
Different-JLG Peers Missed Payment (Nov16)	0.00687	0.00448	0.00319
	(0.00024)	(0.00051)	(0.00033)
Missed Payment (Nov16)	0.26158	0.29316	0.29945
	(0.00144)	(0.00351)	(0.00351)
All Other Controls Included	Yes	Yes	Yes
Religion Indicators	Yes	Yes	Yes
Occupation Indicators	Yes	Yes	Yes
Loan Officer Area FE	Yes	Yes	Yes
Observations	1,745,159	237,698	1,982,862
R-squared	0.486	0.490	0.495

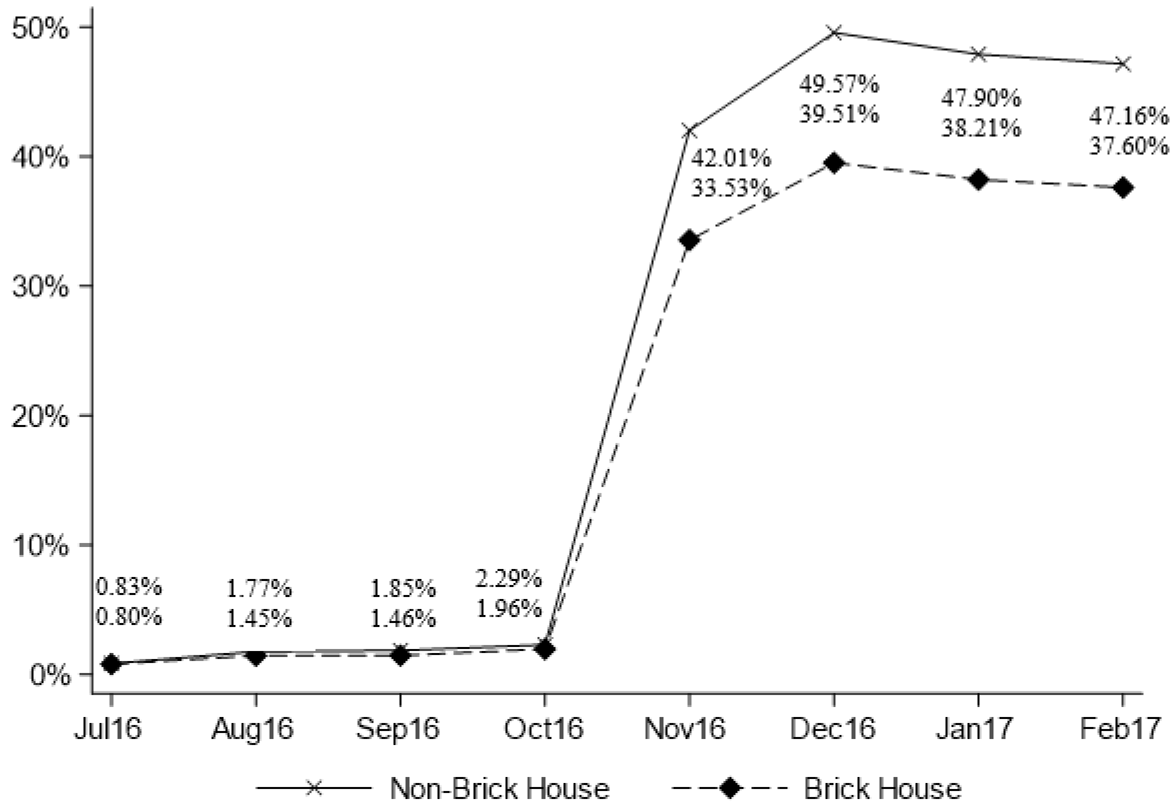
Notes. These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower's missed payments in subsequent months, extending the analysis in Table 2 by now analyzing the effect in 100% repayment centers (Pre Nov16) 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 in the Strength of Peers Influence in New Centers versus Other Centers

	(1)	(2)	(3)
	New Centers	Not New Centers	All Centers
	Missed Payment (Dec16-Feb17)	*Missed Payment (Dec16-Feb17)*	*Missed Payment (Dec16-Feb17)*
Same-JLG Peers Missed Payment (Nov16)			
× New Center			0.00201
			(0.00071)
Different-JLG Peers Missed Payment (Nov16)			
× New Center			0.00179
			(0.00035)
Missed Payment (Nov16)			
× New Center			-0.01826
			(0.00267)
New Center			-0.00742
			(0.00266)
Same-JLG Peers Missed Payment (Nov16)	0.00868	0.00649	0.00636
	(0.00074)	(0.00061)	(0.00053)
Different-JLG Peers Missed Payment (Nov16)	0.00733	0.00654	0.00611
	(0.00038)	(0.00028)	(0.00024)
Missed Payment (Nov16)	0.25618	0.27210	0.27538
	(0.00207)	(0.00173)	(0.00172)
All Other Controls Included	Yes	Yes	Yes
Religion Indicators	Yes	Yes	Yes
Occupation Indicators	Yes	Yes	Yes
Loan Officer Area FE	Yes	Yes	Yes
Observations	962,967	1,019,895	1,982,862
R-squared	0.479	0.498	0.494

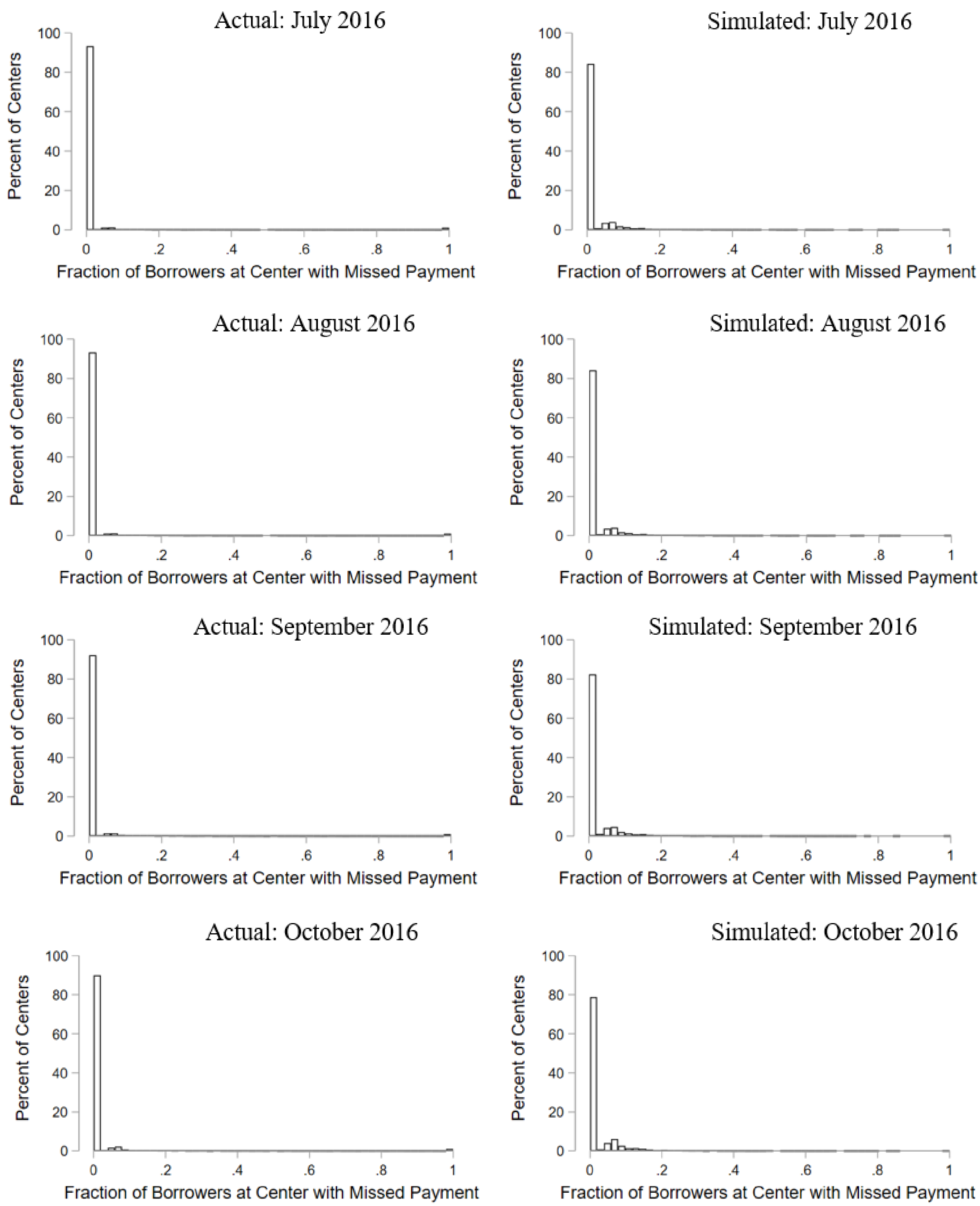
Notes. These regression models examine the effect of same-JLG and different-JLG (but within the same center) peer missed payments in November 2016 on the borrower's missed payments in subsequent months, extending the analysis in Table 2 by now analyzing the effect in new centers (Pre Nov16) vs. other 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.

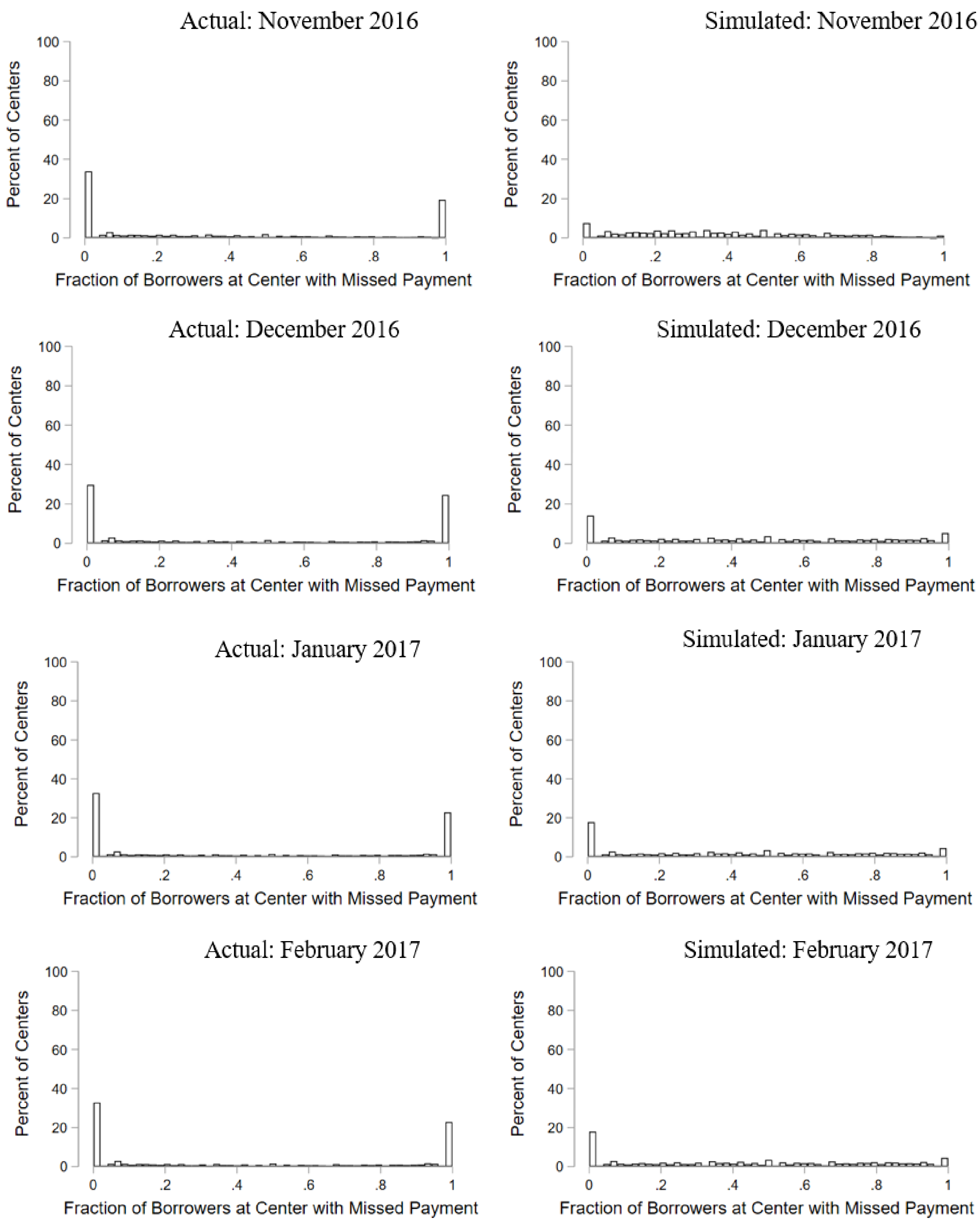
Figure S1. Missed Payment Rates for Borrowers Living in Brick vs. Non-Brick Houses



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.

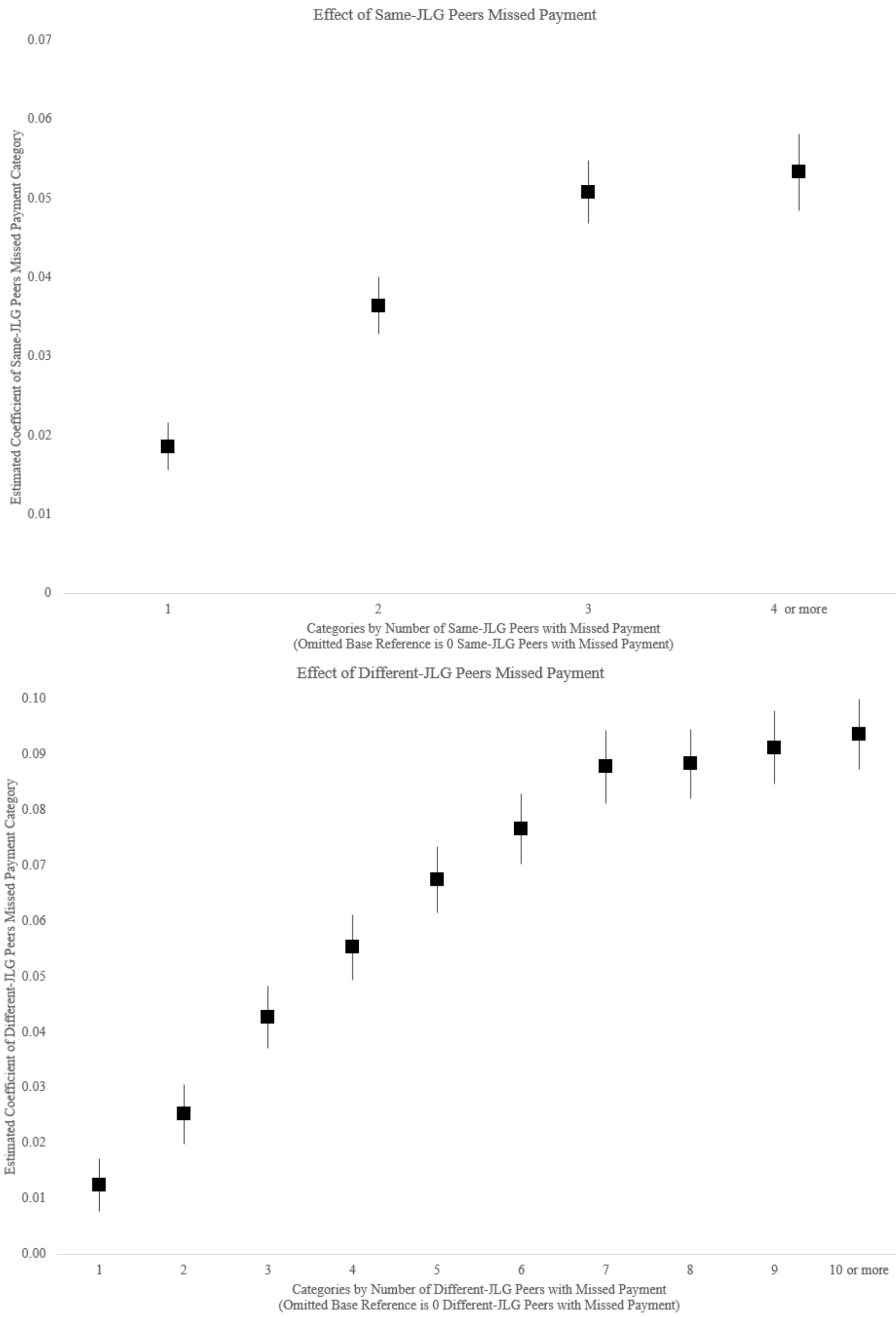
Figure S2. Frequency Distribution of Borrowers with Missed Payment





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 depict visually 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 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.