Credit demand among risk sharing groups under formal insurance: quasi-experimental evidence from Haiti

Aaron Baum [1]

ABSTRACT

How joint liability credit, formal insurance, and informal risk sharing interact is an unanswered question with fundamental implications for poverty alleviation. In this paper, I exploit a natural experiment wherein tens of thousands of microfinance borrowers across rural Haiti received a quasi-random value of insurance benefit in the aftermath of catastrophic hurricanes. The insurance policy combined index insurance for the microfinance institution itself with individual-level indemnity insurance for its borrowers. To feasibly conduct claims review in the low-infrastructure setting of rural Haiti, one borrower per credit center was trained to assess the damages and review the claims of all other borrowers in her credit center. Results suggest that insurance affects formal lending relationships and informal financial ties, and that informal ties within villages influence the allocation of insurance benefits. The central finding is that greater formal insurance makes lending relationships longer and more durable, increasing a beneficiary's demand for credit on the extensive margin. Reciprocally, formal insurance increases the frequency with which a beneficiary changes joint liability groups, reducing the average duration of informal risk sharing relationships. There is no evidence of strategic behavior by claimants or reviewers, in that borrowers were no more likely to submit a claim, nor reviewers more likely to accept a claim, when the potential benefit was quasi-randomly greater. However, I find that being a member of a peer reviewer's joint liability group is associated with a 50% increase in the probability of submitting a claim and receiving a payout. This indicates that differential informal proximity between claimants and peer reviewers may substantially influence within-village allocations. These findings contribute empirical evidence to recent theoretical models of hybrid weather insurance policies that combine group-level index insurance with individual-level indemnity insurance and to the growing literature on how social networks affect and are affected by development interventions.

---

[1]Icahn School of Medicine at Mount Sinai Health System, Department of Health System Design and Global Health, Arnhold Institute for Global Health, email: **aaron.baum@mssm.edu**. I thank Douglas Almond, Emily Breza, James Laguerre, John Mutter, Dan Osgood, Kiki Pop-Eleches, Carine Roenen, and participants at BASIS Assets and Market Access Collaborative Research Support Program's Technical Committee Meetings who provided thoughtful advice, stimulating questions, and sharp feedback. The project was supported through a grant from the USAID Bureau of Economic Growth, Agriculture and Trade's BASIS program and conducted in collaboration with Fonkoze.

1 Introduction

How joint liability credit, formal insurance, and informal risk sharing interact is an unanswered question with fundamental implications for poverty alleviation (Zinman 2015). Prior research has documented the puzzling fact that there is low demand for credit in settings with binding liquidity constraints and large returns to capital (Crépon et al. 2015). While introducing formal insurance should reduce risk and thereby increase investment incentives and demand for credit, it may also effect, and be affected by, informal risk sharing networks, such as joint liability groups (Ghatak and Guinnane 1999; Mobarak and Rosenzweig 2013). The results of this paper suggest that insurance affects formal lending relationships and informal financial ties, and that, reciprocally, informal ties within villages influence the allocation of insurance benefits.

In this paper, I exploit a natural experiment wherein tens of thousands of microfinance borrowers across rural Haiti received a quasi-random value of insurance benefit in the aftermath of catastrophic hurricanes. In particular, conditional on a claim being verified, an individual microentrepreneur with an active line of joint liability credit during a hurricane received a monotonically increasing insurance benefit the earlier the weather shock occurred in her loan cycle. Known in Haiti as "Madam Saras", these entrepreneurs interact with upwards of 90% of all domestic crops, forming the backbone of rural commerce and its value chains (Jolly 1998; N'Zengou-Tayo 1998; Rhodes 2001). The insurance policy was a variant of a "hybrid" index and indemnity based policy, wherein a group-level payout is made based upon a parametric threshold being crossed (to protect against covariate shocks), which is subsequently allocated to individuals within the group through a mechanism that leverages village-level private information about each group members' idiosyncratic component of exposure (Dercon et al. 2014). In this case, the policy combined index insurance for the microfinance institution itself with individual-level indemnity insurance for its borrowers. Helpfully, adoption of the insurance policy was mandated by the microfinance institution, removing any adverse selection driven by endogenous uptake. To operationalize the indemnity-based arm of the policy, one borrower per credit center was elected and trained to assess the damages and review the claims of all other borrowers in her credit center. While leveraging regularly occurring credit center group meetings for claims processing made conducting loss adjustment in the low-infrastructure setting of rural Haiti feasible at low cost, this within-credit center allocation mechanism opened the door for collusion across claimants and reviewers, with incentives strongest when the two share membership in the same joint liability group.

This paper's primary contribution is to show that the hybrid insurance policy increased microfinance borrower's demand for credit along the extensive margin by 15% (from a mean of 47%). This translates to a cross elasticity of demand for credit and insurance of -0.27, signifying that credit and insurance are complements. Because the price of credit did not vary with the value of the insurance, this implies that reducing the price of insurance (increasing the value at a fixed price) shifts the demand curve for credit outward. Further, I exploit the smooth variation in the extent of insurance benefit to generate non-linear estimates, finding decreasing marginal effects of insurance on the demand for credit. I run a variety of placebo and robustness checks that confirm the finding.

A second contribution of the paper is to test for strategic behavior by claimants and reviewers, and a third contribution is to test for collusion in within-village allocations of insurance benefits, using data on joint liability groups as a proxy for informal networks. I find no evidence of strategic behavior in claims submission or review decisions: borrowers were no more likely to submit a (rejected) claim, nor reviewers more likely to accept a claim, when the potential benefit was greater. However, I find that being a member of a peer reviewer's joint liability group is associated with a 50% increase in the probability of receiving a payout. This indicates that differential informal proximity between claimants and peer reviewers may substantially influence within-village allocations. The effect is driven by an increase in the odds of a borrower submitting a claim. Conditional on submission, claims have no greater probability of being verified as a function of informal proximity to the peer reviewer.

A fourth contribution of this paper is to provide insight into the effect of formal insurance on the informal ties underpinning joint liability groups. I find that greater insurance increases the probability that a non-attriting borrower changes joint liability groups over the subsequent three years by 13% (from a mean of 39%). Because increasing the ease with which a borrower can change joint liability groups weakens the threat of a group sanction (e.g. being removed from the group becomes less costly to a borrower), it may increase the probability of strategic defaults. However, I estimate a precise zero effect of the policy on defaults. On the other hand, more frequent switching allows individuals to optimize the composition of their joint liability group over time as a function of private information they learn about group members (e.g. based on repayment and reciprocity histories, exposure to risk and negligence in preventive measures, and so on).

Finally, the individual-level administrative data from the microfinance institution is geotagged at the credit center level, and I model each location's exposure to weather conditions using satellite data on flooding, hurricane wind speeds, and rainfall. I estimate precise zeros for the effects of exposure to extreme weather conditions on subsequent demand for credit or defaults. When I calculate the correlation between the exposure estimated by the weather models and the exposure based on the quantity of claims submitted in a credit center, I find a very weak, positive correlation (generally below .10). To the extent one believes the microdata on claims are a reasonable proxy for individual "ground truth" exposure, this suggests that, for the merchandise and property of small-scale entrepreneurs, the idiosyncratic component of exposure is far more important than the covariate component captured by indices, or else that such indices do not reflect covariate flood risk exposure meaningfully.

This paper adds to the growing literature on the interactions of credit, formal insurance and informal networks (Carter, Cheng, and Sarris 2011; Cole, Giné, and Vickery 2013;

Karlan et al. 2014) by focusing on female microfinance borrowers and indemnity insurance covering merchandise. It also contributes empirical evidence to recent theoretical models of hybrid weather insurance policies that combine group-level index insurance with individual-level indemnity insurance (Clarke et al. 2011). Closest to this paper is Cai et al. (2012), who estimates the average treatment effect of index insurance for crops on rural tobacco farmer's subsequent loan size.[2] Two other related studies are Kanz (2014) and Giné and Kanz (2014), which exploit an eligibility threshold to show that quasi-random debt relief to farmers generated a reallocation of credit *supply* by the bank away from districts that obtained greater relief (where there was also increased strategic default). Like Cai et al. (2012), they estimate the local average treatment effect of insurance on credit markets, rather than marginal effects. Focusing on the influence of insurance on new borrowers, Giné and Yang (2009) show demand for credit among farmers in Malawi declines by 13% when bundled with index insurance in Malawi. Similarly, Banerjee, Duflo, and Hornbeck (2014) show demand for bundled credit and health insurance is far lower than for credit alone.

This paper also contributes to the literature on how social networks affect and are affected by development interventions. Breza (2015) provides a comprehensive review of this literature, including a discussion of prior research on risk sharing networks, peer monitoring and network change.[3] This paper directly contributes to the small but growing literature on the response of informal networks to shocks (such as the introduction of formal insurance) and whether formal and informal borrowing are complements or substitutes (Banerjee et al. 2013, 2015). It also contributes to the literature on peer moni-

[2]Cai et al. (2012) uses a triple difference estimator, comparing changes in loan size across tobacco farmers in districts that were differentially exposed to mandated crop insurance relative to changes in loan size across non-tobacco farmer creditors in the same distinct. Identification rests on (i) a test of common pretrends, however, there are only two pre-treatment periods (years) and she can not include region $\times$ year fixed effects, and on (ii) cleanly separating the supply and demand channels, but ruling out the supply channel is challenging because the loan amount offered and interest rate offered also responded to the instrument.

[3]Most notable is Mobarak and Rosenzweig (2013), who show that whether formal and informal insurance are complements or substitutes depends on basis risk.

toring (Kast, Meier, and Pomeranz 2012; Breza, Chandrasekhar, and Larreguy 2014; Breza and Chandrasekhar 2015) by providing the first study on auditing of insurance claims by members of one's informal network.

Given microfinance institutions reach 200 million households globally, their networked, community-based infrastructure holds promise as a practical platform for delivery of index and indemnity insurance products to rural, poor households. The results from this study, which to my knowledge is the largest study of a joint credit and insurance intervention to date, suggest that one benefit to the microfinance institution of offering insurance is increased demand for credit. However, I find that differential informal financial proximity may systematically bias within group allocations. Because flooding is thought to affect more people than any other disaster category (EM-DAT 2012) and causes damages that are not well modeled with satellite data (Guiteras, Jina, and Mobarak 2015), further research is warranted on risk mitigation products that insure the non-agricultural property of small-scale entrepreneurs against idiosyncratic weather damage, yet still minimize moral hazard, discriminate between justifiable damages and damages due to negligence, and are realistically scalable.

2 Background

This paper investigates the experience of the largest microfinance institution in Haiti, Fonkoze, which in January 2011 began jointly addressing missing insurance markets by providing catastrophic weather insurance to its 60,000 existing borrowers. Fonkoze's mission is to provide the financial and non-financial tools Haitians – primarily women – need to lift their families out of poverty. Fonkoze's "Staircase Out of Poverty" graduation model provides a comprehensive approach to poverty alleviation in Haiti. Each of its four steps is uniquely designed to "provide a woman with the resources and support that she needs to ascend from poverty, wherever she is in her climb" (Fonkoze 2014). Along with the four main steps (starting with an ultra-poor program modeled on BRAC's, two tiered joint liability credit programs with loans ranging from $25 to $1300 USD per person over six months, and individual liability business development loans), Fonkoze also leverages its 2,000 biweekly credit meetings as a platform for education and health services to support borrower households.

In the aftermath of the tragic January 2010 earthquake, the microfinance institution instituted a mandatory natural disaster insurance policy covering all of its borrowers. The product, featured at the 2011 World Economic Forum, was designed to reduce the microfinance institution's portfolio risk to natural disasters while supporting borrower advancement in its graduation model. The hybrid index- and indemnity-based policy covered the institution against rainfall, wind and seismic shocks based on sharp parametric thresholds in geographic regions, and protected the property (merchandise and house) of each borrower through indemnity-based coverage, with claims reviewed by a peer (Tappendorf 2012). As noted, an innovation in product design was training one peer-elected borrower per credit center to process and verify their peer's claims and requiring claimants to declare damages publicly at group credit meetings, thereby leveraging the microfinance institution as a platform for scalable, low cost loss adjustment using village-level, private information (with ad hoc backup from staff auditing teams, when feasible). However, in attempting to insure the property of its borrowers, the payouts from the index-based arm of the product did not match those from the indemnity-based arm of the product, alternately overshooting or undershooting by more than +/- 50% and eventually bankrupting the policy. Despite Swiss Re's reinsurance of the policy, due to insufficient capitalization of the insurer and an unusually harsh hurricane season in the summer and fall of 2012, the indemnity-based component of the insurance policy covering borrowers was unexpectedly discontinued in late October 2012, while the index-based component covering the institution continues. In fact, more than 90% of verified claims paid by the insurance policy were for two huge hurricanes, Hurricane Isaac in August 2012 and Hurricane Sandy in October 2012. These successive hurricanes bankrupted the policy and caused hundreds of millions of dollars of damages and left millions of people in Haiti facing food shortages. I focus on those two extreme weather events in this paper, for which nearly half of the microfinance institution's borrowers submitted a claim.

The key feature of the policy that I exploit for identification is that individual loan forgiveness was the main component of the insurance benefit. In addition to receiving a fixed lump sum payout equal to $125 USD, a verified claim resulted in quasi-random benefits to the individual claimant depending on the percent of time in a policy holder's loan cycle remaining on the date of the weather shock. Even though the loans were provided to groups of 4-5 women who were jointly liable, insurance claims were reviewed at the individual level and insurance benefits were provided to individuals, based on the share of the loan they were responsible for [4]. I use this plausibly exogenous, smooth variation in the extent of the policy's benefit to isolate the marginal impacts of insurance on subsequent demand for credit, estimate spillover effects, explore the dynamic interaction between formal insurance and informal risk sharing groups, test for strategic claims submission, and examine whether differential informal financial proximity to claimants affected the decisions of peer reviewers. In addition, the administrative data provides information at the individual level on claims, reviews, and loan repayment over time that is geotagged at the credit center level, and I model each location's exposure to weather conditions using geospatial data on flooding, hurricane wind speeds, and rainfall to assess the direct effects of weather exposure on the demand for credit and loan defaults.

3 Data

I utilize a combination of administrative records, survey data, and satellite data:

(i) Loan records: Data from the microfinance institution on over 142,234 microfinance borrower's loans over time including loan amount, start and end dates, repayment history, and other information for a selection of quarters between 2010-present. I present

[4] This was pre-defined at the time of the original loan disbursement

summary statistics in Table 1 for the 21,531 clients who submitted a claim and for all 142,234 clients in the data. For those clients submitting a claim, the mean loan size was $249 USD, the mean loan length was 163 days, and the lifetime future default rate was 5.2%.

(ii) Insurance policy records: Data from the microfinance institution on all submitted claims with review decision, payout, and the event's exact date. Additionally, I obtained insurance policy contracts with information on when grid cells were introduced to the index-based arm of the insurance policy and the formula for payout triggers. Table 2 shows summary statistics broken down by hurricane. Note, less than 20% of claims were rejected overall, with a majority of peer reviewers accepting 100% of submitted claims.

(iii) Joint liability groups: I use joint liability group membership as a social/informal network proxy. In order to be eligible for a loan, 4-5 women self-select into a group together and the group that becomes jointly responsible for repaying the full loan amount together (Ghatak 1999).

(iv) Survey data: This data is from a rotating panel of about 1,500 borrowers followed by the microfinance institution who were asked a brief poverty score questionnaire on assets, food security, business activities, children's schooling, etc. every three years since 2005, with household physical characteristics (e.g. roof type, wall type, etc) documented by trained enumerators at the borrower's household. I use the pre-2012 data to test for baseline balance.

(v) Spatial and meteorological data: The geographic coordinates of 1,444 credit centers were provided by the microfinance institution. I use these to proxy for the household location of each borrower. I merge that with satellite collected data on rainfall (Tropical Rainfall Measuring Mission - TRMM), hurricane wind speed (Best Track, Atlantic hurricane database), and flooding (MODerate Resolution Imaging Spectroradiometer - MODIS - Flood Map). For 1,444 credit center point locations, for each hurricane, I calculate the location's cumulative exposure to rain, wind, and flooding as follows:

$$rain_c = \sum_{t=1}^{n} H_{c,t}^{rain} \tag{1}$$

$$wind_c = \sum_{t=1}^{n} (V_{c,t}^{wind})^3 \tag{2}$$

$$flood_c = \sum_{t=1}^{n} I_{c,t}^{flood} \tag{3}$$

where t is daily for rainfall, six hour increments for wind speed, and two day spans for flood, each summed over the duration of a storm. For rainfall, I use Tropical Rainfall Measuring Mission (TRMM) data and calculate H^{rain} for each credit center point based on a bilinear interpolation (distance weighted average) of estimated rainfall (mm) at the four nearest pixels. I use Best Track data (Atlantic hurricane database (HURDAT2) 1851-2015) for hurricane wind speed, which provides at 6 hour intervals the storm center's location and the wind radii around that point for which the wind speed $V_{c,t}^{wind}$ is below 34, between 34-50, 50-64, or above 64 knots, for each quadrant (NE, NW, SE, SW) respectively [5]. I then calculate the distance between the storm's location and each credit center location, and based on which quadrant the center location is in, assign a max wind speed for that time point to the credit center. I follow the literature and sum wind speed cubed over time for a given storm (Hsiang 2010). For flooding, I use MODIS Flood Maps which provides at 2-day intervals an indicator variable $I_{c,t}^{flood}$ equal to 1 if point location c is within a 250x250 meter polygon in the MODIS Flood Map data that was determined to have been flooded at time t. For each polygon, the presence of flooding is determined by estimating deviations of that day's water mask to the average for that polygon.

[5] Thus, there are 4 wind radii values given per quadrant around the storm center's location at a given time.

4 Empirical Strategy

The key feature of the policy that I exploit for identification is that the primary benefit of the insurance payout was loan forgiveness. Accordingly, individuals received differential benefits depending on how much of their loan had already been paid at the time of the weather shock. Individuals who had more recently taken a new loan at the time of the weather event (with a larger amount of loan outstanding) can be compared to individuals who were closer to paying the last installment of their old loans (with a smaller amount of loan outstanding). Breza (2012) uses a similar identification strategy to analyze a large microfinance default episode. This hinges on the assumption that the net benefit (payout minus damages) a borrower received varied quasi-randomly based on when the weather event happened in her loan cycle. Helpfully, the insurance product was mandatory for all borrowers of the microfinance institution, removing the often problematically compounding problems of endogenous uptake and low demand. The main specification is:

$$y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c} \tag{4}$$

where

- $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b has an active loan two (or three) years later
- $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane
- $years_i$ are the number of years individual i has been a borrower of the microfinance institution
- γ_b are branch level fixed effects (there are over 40 branches)
- γ_l are loan officer fixed effects (there are over 200 loan officers)

- $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level (there are over 1,000 credit centers)

I cluster errors at the credit center level because loan cycles of borrowers in the same center are correlated to a greater degree than are loan cycles of borrowers across centers. At the center level, the intraclass correlation of the regressor of interest is 0.38, whereas at the branch level it is 0.025. Results are robust to clustering at the branch level.

5 Results

5.1 Descriptive statistics

Table 1 provides summary statistics of the administrative loan data. There were 57,609 borrowers active during the two major hurricanes in 13,723 distinct joint liability groups across 1,261 credit centers with 220 loan officers based at 46 branches. The mean insurance benefit was \$188 (USD) of loan forgiveness plus a fixed \$125 cash distribution for any verified claim. The average rate of attrition was 47% over two years. Table 2 provides summary statistics of the insurance data. There are some notable patterns that emerge, highlighted in Figure 1. In Hurricane Isaac, 63% of the peer reviewers rejected *zero* claimants and in Hurricane Sandy 86% rejected *zero* claimants. This suggests either (or both) extensive covariate damages at the center level and/or a lack of discrimination in claims review. The claims data indicate widespread damages within and across credit center locations, which stands in contrast to the three geospatial variables based on meteorological data, displayed Figure 2. In fact, using the MODIS Flood Map model and wind speed radii from Best Track data, I find few credit centers exposed to any flooding or hurricane winds. When I aggregate the claims data to the credit center level and calculate the correlation between the exposure estimated by the weather models and the exposure based on the quantity of claims submitted, I find a weak, though positive correlation (generally below .10).

5.2 Baseline balance

Figure 3 is a kernel density plot of $LoanCycleRemaining_i$, the percent of borrower i's loan period remaining on date of the hurricane, which shows that is takes values throughout the interval [0,1). Table 8 shows the results of balance tests, x_i on $PercentLoanCycleRemaining_i$, for a set of demographic variables x_i. Data come from the sub-sample of borrowers across 13 of the 46 branches from whom baseline poverty scorecard data was taken prior to the insurance policy being rolled out. Of the 18 covariates, there is a non-trivial difference across borrowers receiving greater insurance benefit in whether or not meat is frequently eaten in the household. Three other covariates are significantly different by trivial magnitudes and the direction of the difference indicates that, if anything, those borrowers receiving a greater percent of loan forgiven from the insurance policy were less well off at baseline.

5.3 Marginal effect of insurance on demand for credit on the extensive margin

As shown in Table 4 and Table 5, providing full loan forgiveness to microentrepreneurs after severe hurricanes multiplies the odds that a borrower continues to demand credit two and three years later by 2.24 and 1.39 times, respectively. This translate into an absolute percent increase of 15-18% and 8-10% in demand for credit two and three years later, from means of 53% and 24%, respectively. Stated another way, over two years insurance reduces voluntary termination of the lending relationship by about 15-18% in absolute terms, from a mean of 47%. To estimate the marginal effect of insurance on demand and assess whether there are non-linearities in the average treatment effect, I exploit the near continuous variation in insurance benefit. Figures 4 and 5 show results from a kernel-weighted local polynomial regression of $\hat{y}_i$ on $PercentLoanCycleRemaining_i$, where $\hat{y}_i$ is the linear prediction of the regression $y_{i,c,l,b} = \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$. As shown in the figures, there are decreasing marginal returns to the share of loan forgiven. The first quartile of insurance benefit boosts demand for credit by over half the average treatment effect, with marginal effects flattening out as the insurance value increases.

5.4 Cross elasticity of demand for credit and insurance

I calculate, $\varepsilon_{credit,insurance}$, the cross elasticity of demand for credit and insurance as follows:

$$\varepsilon_{credit,insurance} = \frac{dx_{credit}}{dp_{insurance}} * \frac{p_{insurance}}{x_{credit}} \tag{5}$$

where x is the quantity of credit demanded and p is the price of insurance, which I calculate as $p_{insurance} = v^{-1}_{insurance}$, the inverse of the value of insurance v. The value of insurance varied between zero and 100% loan forgiveness over a fixed price. I use the range of 25% to 75% in this calculation, within which the value increases by a factor of 3. I assume that increasing the insurance value by a factor of $k = 3$ at a fixed price is equivalent to reducing the price by a factor of $\frac{1}{k} = \frac{1}{3}$ at a fixed value, to arrive at a percent reduction in its price of $dp_{insurance}/p_{insurance} = \frac{1}{3} - 1 = -\frac{2}{3}$. To calculate dx_{credit}, I take the predicted values $\hat{y}(PercentLoanCycleRemaining)$ from the main regression reflecting demand for credit at benefit level $PercentLoanCycleRemaining = .75$ and $.25$, which are .647 and .749, respectively, and calculate dx_{credit} as their difference, .102. For x_{credit}, I use the predicted value of demand $\hat{y}(PercentLoanCycleRemaining < .05)$, when the level of insurance is less than 5%, which equals .567. The cross elasticity of demand, $\varepsilon_{credit,insurance}$, is thus:

$$\varepsilon_{credit,insurance} = \frac{\hat{y}_{.75} - \hat{y}_{.25}}{\frac{1}{3} - 1} * \frac{1}{\hat{y}_{.05}} = \frac{(.749 - .647)}{(-.667)} * \frac{1.000}{.567} = -0.266 \tag{6}$$

5.5 Attributing effects to voluntary termination

As shown in Table 6, greater insurance benefit does not increase or decrease default rates: I estimate a precise zero with a 95% confidence interval (-0.01,0.02). As a rule, non-defaulting borrowers are eligible for subsequent loans based on microfinance institution policies per its graduation model. Thus, the observed reduction is from voluntary termination by the borrower.

5.6 Spillover effects

As shown in Table 7, I find that effects of insurance on demand for credit appear to spill over onto social ties of beneficiaries. The spillover effect is 80% the magnitude of the main results. Results are similar whether estimating effects for the sample of all joint liability group members of a borrower who benefited from the insurance, or when restricting the sample to only those group members who made no claim against the insurance policy, or to only those social ties who made at least one claim. I interpret this peer-effect with caution, though, because (i) it is partly a mechanical result of the joint liability nature of the loan; and (ii) three year results do not show a similar pattern.

5.7 Testing for strategic claims submission and review

One would expect (duplicitous) borrowers with larger potential payouts to file (false) claims of damages more often than borrowers with less to benefit. If undetected, borrowers earlier in their cycle would tend to receive a larger net benefit than borrowers later in their cycle, simply due to differential incentives for submitting (false) claims. As Table 8 shows, I find no evidence of strategic claims submission. Borrowers were not more likely to submit a claim when the potential benefit was (quasi-randomly) greater. Under the testable assumption that the claims review decision did not vary systematically with the size of the potential payout, this imply that borrowers with more to gain were not more likely to submit false claims. As Table 9 shows, this assumption holds: reviewers were very slightly (1%) more likely to accept a submitted claim when the potential benefit was (quasi-randomly) greater, but the 1% magnitude is very small relative to the mean acceptance rate of 80% and 94% for Hurricane's Isaac and Sandy, respectively.

5.8 Testing for reviewer bias due to informal financial ties

As shown in Table 10, analysis of peer-based claims review shows borrowers who were in the claim reviewer's joint liability group had 1.47 greater odds of submitting a claim, off of a baseline of 37%. Conditional on submission, claims from joint liability group members of the reviewer were not significantly more or less likely to be verified (Table 11). This indicates that informal financial proximity may bias the review process at the level of claims submission. However, omitted variables (such as geographic distance between households) may be correlated to both a borrower's choice to select into her joint liability group and her propensity to submit a claim. I therefore interact an indicator variable for whether a borrower is in the joint liability group of the claims reviewer with the instrument used in the main analysis reflecting the percentage of a borrower's loan period left at the time the weather event happened. Under this specification, shown in Table 12, I estimate a non-significant 1.15 coefficient (odds ratio) on the interaction term, reflecting an increased probability of submitting a claim for borrowers with greater potential benefit who are in the joint liability group of the reviewer. However, I can not reject the null hypothesis that the interaction term's coefficient (odds ratio) is 1.0.

5.9 The interaction of formal insurance and informal networks

All non-attriting borrowers either remained in the same joint liability group over time that stayed in tact or her group dissipated and she joined a new group. When restricting the sample to non-attritors, I show in Table 13 that greater insurance benefit multiplied the odds of a borrower switching joint liability groups over the subsequent three years by 2.6, from a median of 1 switch per borrower. Considering joint liability groups as a vehicle for informal risk sharing, this suggests that, rather than necessarily crowding-in vs. crowding-out informal insurance, formal insurance makes informal insurance networks more liquid.

5.10 Effect of insurance on the intensive margin

Because the instrument affects the extensive margin of demand (e.g. it reduces attrition), I restrict the sample to non-attritors when investigating effects on intensive margin. As shown in Table 14, when restricting the sample to non-attritors, I find that, relative to no insurance benefits, full insurance benefits reduces the amount of credit disbursed (loan size) two years later by \$20 USD ($p < .10$). I find no effect on loan size three years later. Similarly, when again restricting the sample to non-attritors, relative to no insurance I find that full insurance benefits reduces the amount of savings (e.g. collateral, a direct function of loan size) by \$9 USD ($p < .05$) two years later. I find no effect on savings amount three years later. Finally, as shown in Table 15, I show that full insurance benefits increase the odds of delinquency, defined as being at least 90 days late on a loan, among non-attritors two years later by 1.39, from a baseline of 37%, and increases the average number of days delinquent by 23 days, from a mean of 59 days. I find smaller effects on delinquency and days late three years later.

5.11 Weather impacts on demand for credit and defaults

I estimate the effect of exposure to rainfall, hurricane winds, and floods on attrition using the following specification:

$$y_{i,c,l,b} = \kappa_1 + \kappa_2 WeatherExposure_c + \gamma_b + \gamma_l + \varepsilon_{i,c} \tag{7}$$

where $WeatherExposure_c$ is equal to $wind_c = \sum_{t=1}^{n} (V_{c,t}^{wind})^3$, $flood_c = \sum_{t=1}^{n} I_{c,t}^{flood}$, or $rain_c = \sum_{t=1}^{n} H_{c,t}^{rain}$, as defined in Section 2.3. As shown in Table 16, I find zero effect of exposure to rainfall, hurricane winds, and floods on demand for credit two years later. Over three years, I find a precise zero effect of exposure to rainfall and winds, but flood exposure *increases* the probability a borrower remains active three years later by 2-4% ($p < .05$). There is, however, no evidence of heterogeneous effects of insurance benefits based on weather exposure. That is, when the dependent variable is demand for credit three years later the coefficient is a precise zero on the interaction of flood exposure $\times$ insurance benefit).

6 Robustness checks

As noted, my identification strategy is based on the fact that the (random) timing of the weather shock determines the value of insurance benefit a borrower receives. If the weather event happens early in a borrowers loan cycle, for example the day after her loan period began, then her entire loan forgiven if she submits a claim and it is verified. In contrast, if the weather shock occurs just before the end of her loan cycle, then the amount of loan forgiveness she receives is very close to zero. The identifying assumption is that the net change in a borrower's wealth, equal to the amount of debt forgiven minus her loss in wealth due to damages inflicted by the weather shock, varies only due to the time during her loan cycle when the weather event occurred.

6.1 Threats to the identifying assumption

There are a variety of threats to this identification strategy. Lesser threats include (i) Endogenous uptake: which is not a problem in this case because insurance adoption was mandatory; (ii) Endogenous loan start dates or length: which is not a problem in this setting because the variation in gaps between loan cycles is quite small and the lengths of loan cycles are fixed; (iii) If borrowers delay repayments to game potential benefits: helpfully, the benefit for a verified claim was not based on loan amount outstanding (disbursed amount minus repaid amount to date), but rather the percent of the loan period remaining on the date of the weather shock. Furthermore, the microfinance institution requires piecemeal loan repayment to reduce its default risk. But even if a borrower did delay making repayments until a lump sum at the end of their cycle, rather than smoothly, she received the same benefit as if she had been current; (iv) Strategic claims submission: one might expect borrowers with larger potential payouts to file (false) claims of damages more often than borrowers with less to benefit. As discussed above, Table 9 shows there is no evidence of endogenous claims submission as a function of the instrument; (v) Endogenous claims review as a function of the instrument: as discussed above, Table 9 shows that reviewers were 1% more likely to accept a submitted claim when the potential benefit was (quasi-randomly) greater. However, the 1% magnitude is not meaningful in relation to the mean acceptance rate of 80% and 94% for hurricanes Isaac and Sandy, respectively; (vi) Early cycle borrowers may be more often brand new borrowers, relative to late cycle borrowers (Breza 2012), and if so, as a group they may be different (e.g. poorer or less committed to the microfinance institution, so more likely to make false claims): thus I drop all observations of borrowers in their first loan cycle and rerun the main specification. Results do not change; and (vii) Bias in claims submission or review due to informal financial ties: as Table 10 shows, there is evidence of greater claims submission based on informal financial proximity to the reviewer, but conditional on submission, claims from borrowers socially proximate to the reviewer were no more or less likely to be verified (Table 11). Reassuringly, this will not cause biased estimates because the instrument is independent of whether or not a client is socially proximate to the reviewer (see Table 17, column 1). I also run two additional specifications to confirm this: I add a control variable for financial proximity (an indicator for a borrower being in the reviewer's joint liability group or not) to the main specification and, in addition, also add an interaction term for informal financial proximity $\times$ insurance benefit. I find no evidence of heterogeneity of treatment effects by informal financial proximity (results are shown in Table 17, columns 2 and 3). Two greater threats to identification are (i) whether a borrower's loan cycle is correlated to damages to merchandise; and (ii) whether the percent of time elapsed in a borrowers' loan cycle is mechanically correlated to attrition in the absence of any insurance benefit, both of which I discuss in the following subsections.

Whether loan cycle is correlated to damages to merchandise

As noted above, the benefit for a verified claim was not based on amount of loan outstanding, but rather the percent of a borrower's loan period remaining at the time of the hurricane. Thus, even if borrowers delay making repayments until a lump sum at the end of their cycle, rather than smoothly, they receive the same benefit. However, to the extent that the amount of actual damages (e.g. merchandise destroyed) was larger for borrowers earlier in their loan cycle, they received larger loan forgiveness but also experienced larger damages. Whether this would offset the size of the variation in net benefit across borrowers who were early vs. late in their loan cycle depends on whether the amount of merchandise in stock (e.g. at risk of damage) is strongly correlated to the percent of a borrower's loan period remaining. This depends on whether, on average, borrowers spend their loan in a lumpy manner (immediately using the whole loan at once) or in a smooth manner (over the entire loan cycle in small pieces). Importantly, even in the case that damages are correlated to the loan cycle, that would cause the net wealth change (benefit – loss) to vary less across early and late cycle borrowers, which will reduce the power of the instrument and bias results downward (against rejecting the null). I have included this question in a survey that is currently wrapping up, but without further information, the best option is to make the weakest assumption possible: that the pattern of loan use is heterogeneous. I assume some borrowers will use loans all at once immediately and some will use it piecemeal over the repayment period's full duration. Thus, in aggregate borrowers use their loan over the whole cycle, but more of it early on. In this scenario, the key assumption of my identification strategy holds that early-cycle borrowers receive a larger net benefit than late-cycle borrowers due to the random timing of the weather event in their cycle.

Placebo tests of whether percent loan cycle remaining is mechanically correlated to attrition

The number of borrowers with an active loan during the two hurricanes equals 57,609, however only 21,531 made a claim. I use the borrowers in joint liability groups whose members made no claim as a "placebo cohort" on which I run placebo tests to examine whether the percent of time elapsed in a borrowers loan cycle is correlated to attrition in the absence of any insurance benefit. It is plausible effects could be non-zero in either direction. Borrowers early in their cycle have more lead time before their current loan ends, so mechanically they can not in fact attrit until later than borrowers late in their cycle. Carrying this forward over cycles, we might expect early cycle borrowers to be less likely to attrit even two and three years later. Alternatively, borrowers late in their cycle have already repaid most of their loan and thus are less likely to default in that cycle relative to borrowers early in their cycle, making them less likely to attrit. I run the main specification on borrowers who were active during the hurricane but made no claim. I do find that being earlier in one's cycle leads to a small yet significant increase in the probability a borrower remains active two or three years later of 4.8% ($p < .01$) and 1.9% ($p < .10$), respectively, shown in Table 18 columns 1 and 2. The magnitude is less than one third of the average treatment effect I find in the main specification.

As a consequence, I next run a specification using the "placebo cohort" (borrowers in joint liability groups whose members made no claim) as a control group, as follows:

$$\begin{aligned} y_{i,c,l,b} = \delta_1 + \delta_2 LoanCycleRemaining_i + \delta_3 MadeClaim_i \\ + \delta_4 LoanCycleRemaining_i \times MadeClaim_i + \delta_5 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c} \end{aligned} \tag{8}$$

with δ_4 the coefficient of interest estimating the effect of greater insurance benefit on the probability the borrower remains active, and where $MadeClaim_i = 1$ when borrower i made a claim and 0 otherwise. This specification removes the "placebo effect" found above from estimated coefficients. As shown in Table 19, results are similar to the main specification. The magnitude of the effect of insurance benefit on the probability the borrower remains active two or three years is 11% and 6% in absolute terms ($p < .001$), respectively, compared to 15% and 8% in the main specification (from means of 53% and 24%). I conduct the same placebo test for other outcomes, including defaults, whether a borrower switches joint liability groups over the subsequent three years, and the number of distinct joint liability groups they belong to over time. Reassuringly, as shown in Table 18, I continute to find precise zeros.

6.2 Restricting sample to span of time just before a loan cycle started or just after loan cycle ended

I restrict the sample to borrowers who received a benefit of 80% of their loan amount or greater and those who received a benefit of 20% of their loan amount or less, then run the following regression:

$$y_{i,c,l,b} = \alpha_1 + \alpha_2 EightyPercent_i + \beta_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c} \tag{9}$$

with $EightyPercent_i = 1$ if borrower i had eighty percent or more of their loan cycle remaining when the hurricane occurred. As shown in Table 20, results and significance levels are unchanged from the main specification despite the smaller sample size. While one might expect the coefficient to be larger when comparing borrowers who received nearly no benefit to those who received the greatest benefit, as implied by Figure 4, this is offset by the observed decreasing marginal returns to the benefit.

7 Discussion

The results of this paper suggest that insurance affects lending relationships and informal financial ties, and that informal ties influence within village allocations of insurance payouts. Greater insurance coverage makes formal lending relationships longer and more durable, increasing a beneficiary's demand for credit on the extensive margin. To the extent a longer lending relationship provides the microfinance institution with exclusive information about a borrower's quality, this translates into a competitive advantage that accrues over time. Such an informational advantage is particularly relevant when lending to small firms with uncertain profits in developing economies where credit histories are scarce. Reciprocally, in increasing the frequency with which a beneficiary changes joint liability groups, formal insurance reduces the average duration of informal risk sharing relationships. Encouraging such groups to update their composition based on private information they learn over time (e.g. about individual exposure to risk and reciprocity histories) may have positive consequences for how effectively the arrangement mitigates risk over time, but it also weakens the threat of a group sanction to any member. While there is no evidence of strategic behavior by claimants or reviewers, I do find that being informally connected increases the probability of receiving a payout by 50%, due to an increase in the odds of claims submission yet no effect on claims review conditional on submission.

A first limitation of this study is that I do not observe total lending, only lending with one microfinance institution. While it is the largest microfinance institution in rural Haiti, it is certainly plausible that some of the attritors obtained formal loans from other banks after their relationship with this microfinance institution ended. To the extent attritors replaced their credit with a competitor's credit, the result reflects less the demand for credit and more switching between creditors. A second limitation is that I only observe previous borrowers' decision to renew loans, not the decision of new borrowers to take up first-time loans with the microfinance institution. Though existing borrowers are better informed than new borrowers about the value of microcredit, and thus their demand response is perhaps more reflective of its true value, expanding the volume of borrowers served is a major goal of microfinance institutions from both a business and mission perspective. A third limitation is that all borrowers I analyze received some insurance benefit. Thus, this study can only speak directly to the average and marginal effects of greater vs. less coverage.

There are two important clarifications worthy of discussion. First, I claim the observed increase in renewal of lending contracts represents an increase in the demand for credit, rather than an increase in the supply of credit. I separate the two channels based on the precise zero effect I estimate on defaults, coupled with the assumption that the microfinance institution policy of offering all non-defaulting borrowers subsequent loans was followed. If the policy was only weakly enforced, the magnitude of my estimates may be biased upward; however, to confound inference, the probability the bank did not offer a subsequent loan to a non-defaulting borrower would have to be correlated to the percent of that borrower's loan period remaining at the time of the hurricane, which is highly unlikely. Second, I find small effects of greater insurance on the intensive margin, including for loan size (decreases it), savings (decreases it), and delinquency rates (increases it), which are surprising given the direction of the main finding. However, the microfinance institution provides loans sequentially, with the amount offered a function of the number of prior loan cycles a borrower has completed, therefore there is little to no borrower choice in loan size. In addition, because a minimum savings deposit is required for collateral (equal to a percent of the loan size) but is rarely updated beyond the initial deposit, in this setting changes in savings essentially reflects changes in loan size.[6] The increase in delinquencies is, however, surprising. It is worth noting, though, that it only reflects variation among borrowers who continued their lending relationship, which itself depended on the insurance benefit, making the finding less straightforward interpret.

8 Conclusion

This study shows that the demand for credit is increasing in the value of insurance (by 15% in absolute terms, from a mean of 47%) and that insurance has decreasing marginal effects on the demand for credit. I calculate a negative cross elasticity of demand for credit and insurance (of -0.27), which indicates the goods are complementary. I also show that greater insurance substantially increases the frequency of borrower's switching joint liability lending groups. Additionally, I find that borrowers were no more likely to submit a (false) claim, nor reviewers more likely to accept a claim, when the claimant's potential benefit was quasi-randomly greater. However, I do find evidence consistent with collusion based on informal financial proximity. The odds that a member of the peer reviewer's joint liability group submitted a claim was 1.47 times greater than the odds that a borrower not in the reviewer's joint liability group did, yet conditional on submission, both claims had

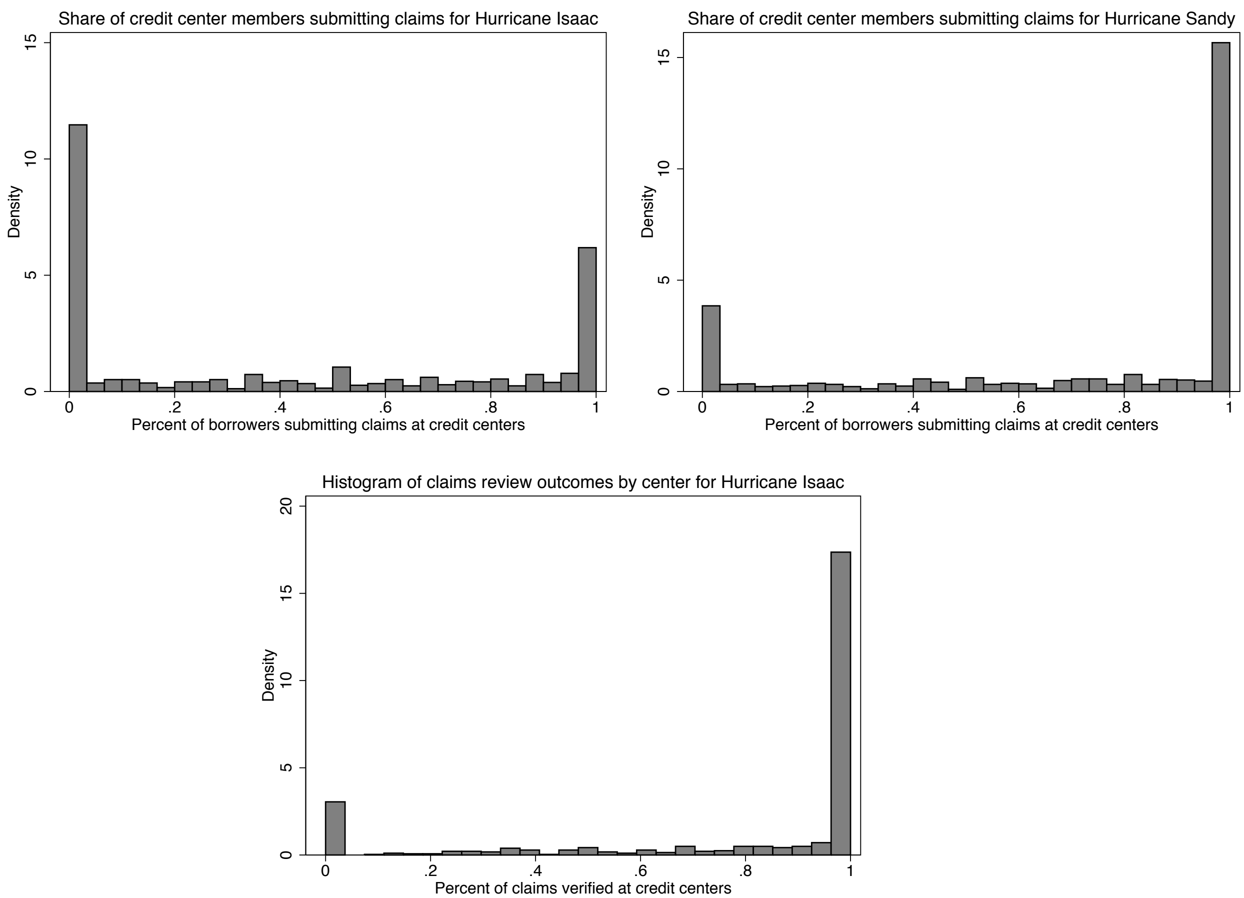
[6]This is consistent with prior studies (Cai, 2015; Kanz, 2015) find zero effects on savings from greater insurance.

the same probability of being verified.

The policy implications of these findings are promising, with caveats. A first-order question for any microfinance institution is whether the benefits to the institution gained from assessing individual-level claims after natural disasters rather than using an index (e.g. reduced payouts) outweigh the higher implementation costs of labor-intensive loss adjustment. Based on this study, the benefit to a microfinance institution is more durable, longer lending relationships. On the other hand, I find that differential informal financial proximity results in systematically biased loss adjudication by peers. It is thus important to conduct further research on whether incentives and credible threats, such as audits, can reduce reviewer bias due to informal financial ties.

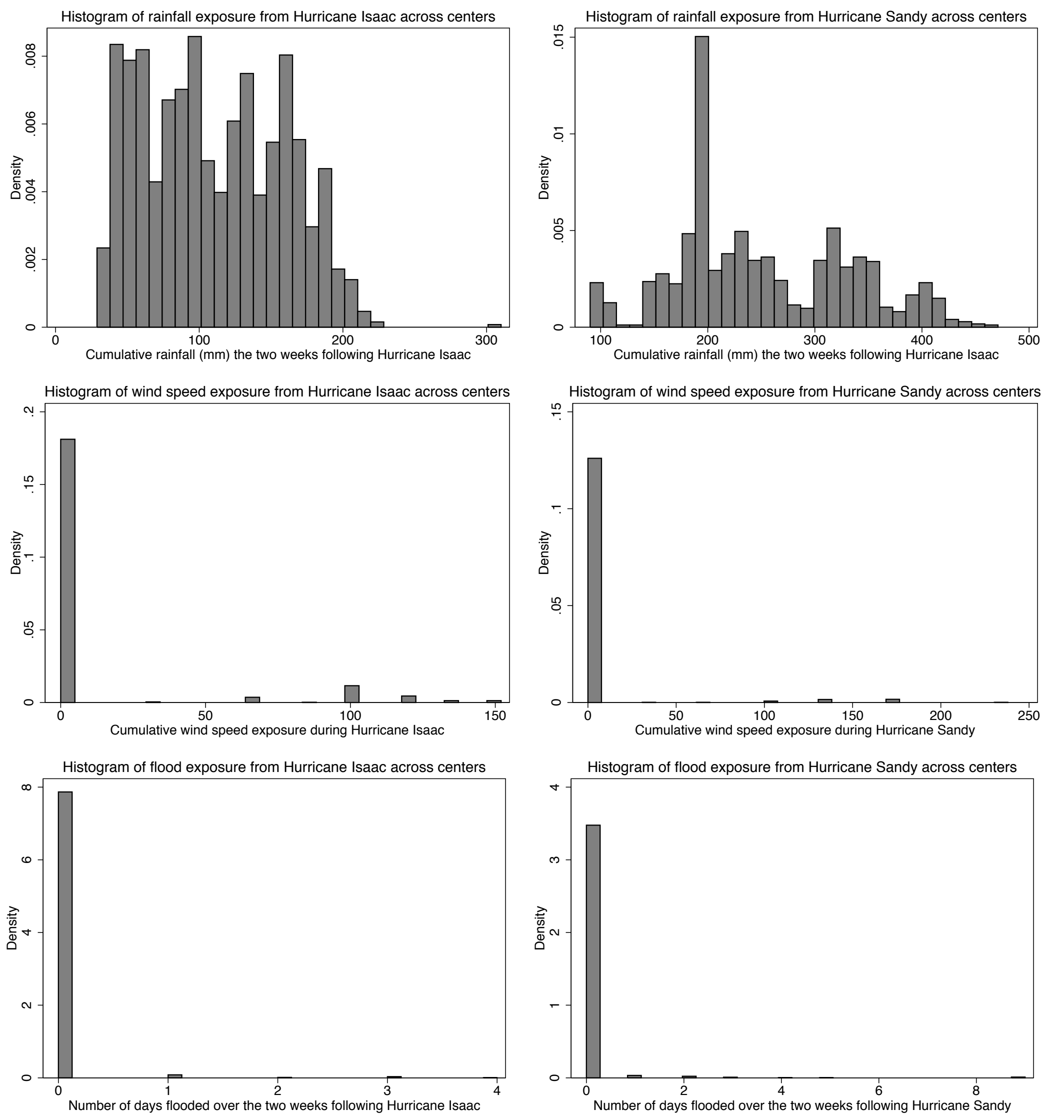
Despite these limitations, the costs to a microfinance institution of using regular credit center meetings as a scalable platform for peer-based indemnity insurance are marginal. In contrast to the challenge of accurately estimating the damages to the property of entrepreneurs with an index, peers can leverage their private information to assess claims among their social network. Because the scale of property (e.g. farm plot area) decreases with wealth, basis risk will generally increase with poverty, a shortcoming especially relevant to poor microentrepreneurs who seek protection against damages to merchandise rather than fields of crops. Such entrepreneurs form the backbone of rural commerce in Haiti and many other developing countries and have a need for insurance products that reduce their exposure to risk yet are realistically scalable.

Figure 1: Distribution of claims submission and rejection rates across credit centers



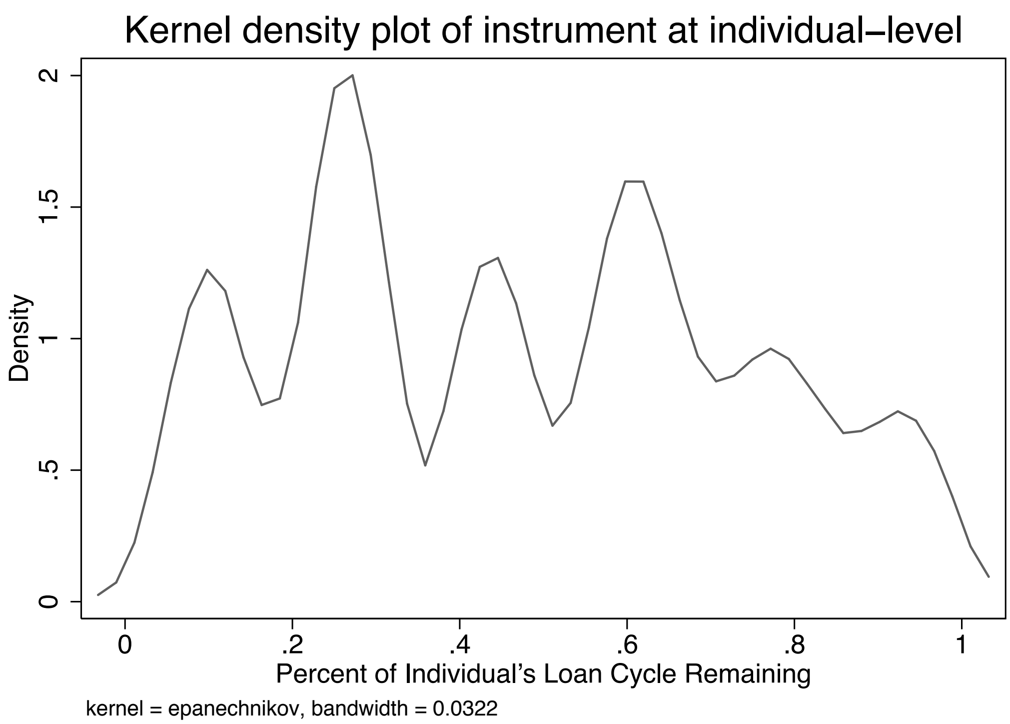
Distribution of the percent of claims submitted (top) and verified (bottom) across center chiefs for Hurricane Isaac (left) and Sandy (right).

Figure 2: Distribution of exposure to rainfall, hurricane windspeed, and flooding across credit centers



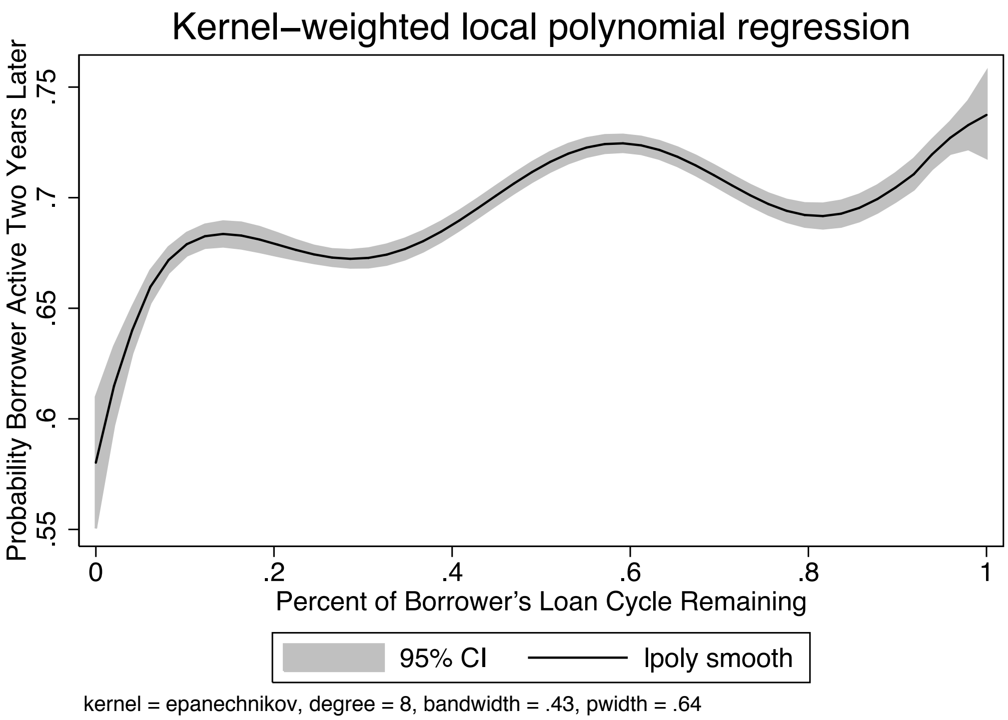
Distribution of exposure to rainfall, hurricane wind speeds (above 34 knots), and flooding across credit centers using TRMM, Best Track, and MODIS Flood Map models spatially matched to credit center latitude and longitude locations.

Figure 3: Distribution of $LoanCycleRemaining_i$ across borrowers



Distribution of $LoanCycleRemaining_i$, the percent of borrower's loan period remaining on date of hurricane, among borrowers who submitted a claim.

Figure 4: Non-linear effects of insurance benefit on demand for credit two years later



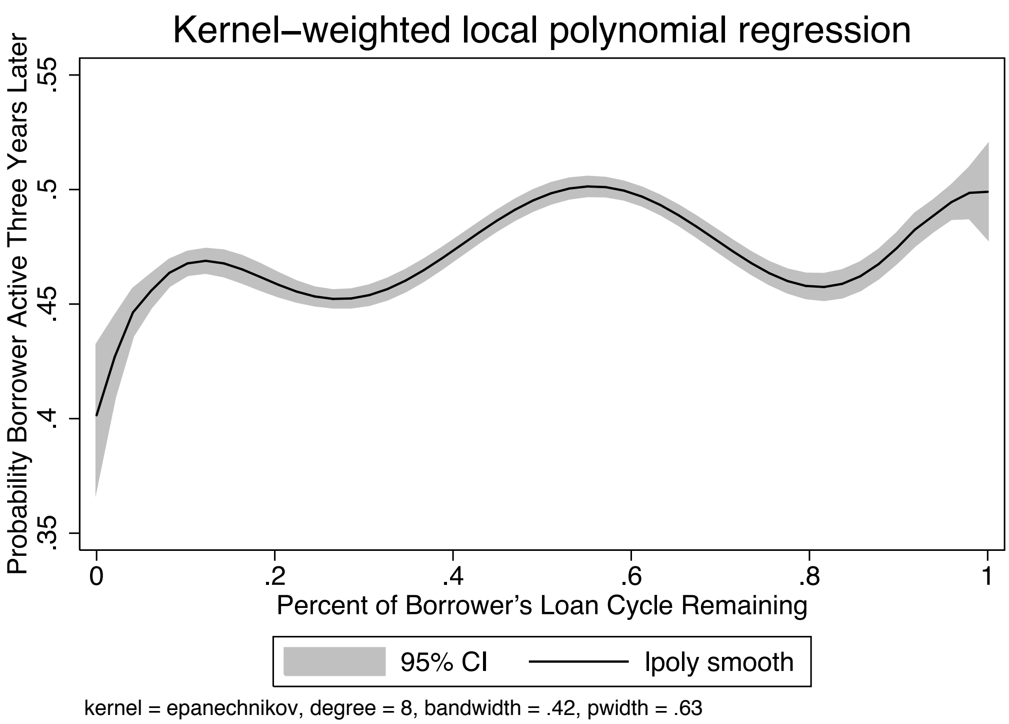
.

.

This figure shows the smoothed values of a kernel-weighted local polynomial (degree 8) regression of $\hat{y}$, which is the linear prediction of regressing $y_{i,c,l,b}$ two years later on $years_i$, γ_b, and γ_l, on $PercentLoanCycleRemaining_i$, the percent of the borrower's loan cycle remaining when the hurricane struck

Figure 5: Non-linear effects of insurance benefit on demand for credit three years later

.



.

This figure shows the smoothed values of a kernel-weighted local polynomial (degree 8) regression of $\hat{y}$, which is the linear prediction of regressing $y_{i,c,l,b}$ three years later on $years_i$, γ_b, and γ_l, on $PercentLoanCycleRemaining_i$, the percent of the borrower's loan cycle remaining when the hurricane struck

Table 1: Descriptive statistics on loan data

	Submitted claim during hurricanes	All loans in data
Number of borrowers	21,531	142,234
Number of JLGs	6,965	42,457
Number of credit centers	1,236	1930
Number of loan officers	159	524
Number of branches	40	50
Mean loan disbursement amount	$249	$301
Mean loan forgiveness	$118	N/A
Median loan length (days)	163	155
Percent loans in default	5.2%	4.5%
Mean number of JLG changes per customer	1.43	1.22

Table 2: Descriptive statistics on insurance data

	Hurricane Isaac	Hurricane Sandy
Number of active clients during hurricane	50,652	49,371
Number of claims submitted	12,242	15,782
Number of claims accepted	8,128	13,452
Number of claims rejected	4,114	2,330
Mean percent of claims submitted per center	42%	71%
Mean percent of claims accepted per center	80%	94%
Mean percent of claims rejected per center	20%	6%
Number of centers with any claims	762	1,066
Number of centers with zero rejected claims	482	921
Number of centers with zero accepted claims	86	37
Number of centers with at least one rejection and one acceptance	194	108

Table 3: Balance tests: $x_{i,c} = \beta_1 + \beta_2 PercentLoanCycleRemaining_i + \varepsilon_{i,c}$

x (pre-2012 outcome)	β_1	β_2	*p-value*
Loan Amount (USD)	102.80	6.60	.332
Savings	21.22	3.85	.113
PPI Score	36.61	-.02	.991
Food Security	4.55	-.33	.289
Tin Roof	.97	-.07	.011**
Cement floor	.68	-.00	.943
Own house	.69	.07	.154
Own land	.65	.07	.182
Latrine	.70	-.03	.533
Bed	1.00	-.08	.001***
Electricity	.11	.01	.853
Small assets	.61	.00	.942
Garden	.80	.00	.937
Partner	.75	.015	.723
Literate	.67	.00	.992
All children in school	.83	-.08	.047**
Eat meat frequently	.29	.15	.002***
Received remittance	.18	.01	.793
Observations	1,326	1,326	1,326

Balance tests showing the coefficients and significance levels from the regression $x_{i,c} = \beta_1 + \beta_2 PercentLoanCycleRemaining_i + \varepsilon_{i,c}$ for covariates $x_{i,c}$. Data come from the sub-sample of borrowers across 13 of the 46 branches from whom baseline poverty scorecard data was taken prior to the insurance policy being rolled out.

Table 4: Effect of insurance benefit on demand for credit

	Active two years later (OR)	Active three years later (OR)	Active two years later (OR)	Active three years later (OR)
Percent of borrower's loan period	2.65***	1.51***	2.24***	1.39***
remaining on date of hurricane	(.299)	(.138)	(.233)	(.121)
Years a borrower	1.12***	1.19***	.939	1.10**
	(.038)	(.065)	(.071)	(.064)
Constant	1.121	.235**	1.044	.279**
	(.389)	(.134)	(.558)	(.180)
Branch FE	Yes	Yes	Yes	Yes
Loan officer FE	No	No	Yes	Yes
Observations	21,589	21,589	21,570	21,570

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratio coefficients, standard errors, and significance levels from the logistic regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b has an active loan two (columns 1 and 3) or three (columns 2 and 4) years later, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects (included only in columns 3 and 4), $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 5: Effect of insurance benefit on demand for credit

	Active two years later	Active three years later	Active two years later	Active three years later
Percent of borrower's loan period remaining on date of hurricane	.179***	.098***	.154***	.078***
	(.023)	(.021)	(.020)	(.020)
Years a borrower	.022***	.041***	-.011	.021
	(.014)	(.013)	(.014)	(.013)
Constant	.530***	.235***	.501***	.201***
	(.075)	(.131)	(.124)	(.137)
Branch FE	Yes	Yes	Yes	Yes
Loan officer FE	No	No	Yes	Yes
Observations	21,589	21,589	21,589	21,589

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the linear regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b has an active loan two (columns 1 and 3) or three (columns 2 and 4) years later, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects (included only in columns 3 and 4), $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 6: Effect of insurance benefit on default rates

	Default	Default
Percent of borrower's loan period remaining on date of hurricane	-.003	.005
	(.010)	(.009)
Years a borrower	.002	.006
	(.006)	(.006)
Constant	.185**	.085***
	(.092)	(.032)
Branch FE	Yes	Yes
Loan officer FE	No	Yes
Observations	21,589	21,589

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the linear regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b defaulted over the subsequent three years, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects (included only in column 2), $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 7: Peer effects of insurance benefit on demand for credit two years later

	All group members	Group members who made claim	Group members who made no claim
Percent loan period remaining	.122***	.100***	.180***
	(.019)	(.022)	(.063)
Years a borrower	.003	-.004	.039
	(.014)	(.016)	(.029)
Constant	.317***	.468***	.364***
	(.086)	(.133)	(.119)
Branch FE	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes
Observations	22,999	16,792	3,193

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the linear regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b remained an active borrower over the subsequent two years, $LoanCycleRemaining_i$ is the percent of borrower i's joint liability group member's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level. Column 1 is restricted to the sample of all joint liability group members of a borrower who benefited from the insurance (excluding the claimant borrower herself). Column 2 further restricts the sample to only those joint liability group members who made no claim against the insurance policy, whereas Column 3 further restricts the sample to only those joint liability group members who made at least one claim (again, excluding the claimant borrower herself).

Table 8: Effect of potential benefit on claims submission

	Borrower submitted claim (OR)
Percentage of borrower's loan period remaining on date of hurricane	1.071
	(.079)
Years a borrower	1.200***
	(.049)
Constant	.231***
	(.083)
Branch FE	Yes
Loan officer FE	Yes
Observations	48,937

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratio coefficients, standard errors, and significance levels from the logistic regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b submitted a claim for damages due to Hurricane Isaac or Sandy, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 9: Effect of potential benefit on claims review decision

	Reviewer accepted claim (OR)	Reviewer accepted claim (linear)
Percentage of borrower's loan period remaining on date of hurricane	1.35**	.014**
	(.196)	(.007)
Years a borrower	.498***	-.031***
	(.059)	(.005)
Constant	.318***	1.119***
	(.118)	(.019)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	21,811	25,139

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratios (column 1) and coefficients (column 2), standard errors, and significance levels from the logistic (column 1) and linear (column 2) regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b had a claim accepted, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 10: Effect of informal financial ties on claims submission

	Borrower submitted claim (OR)	Borrower submitted claim (linear)
Reviewer in lending group	1.47***	.062***
	(.105)	(.010)
Years a borrower	1.246***	.029***
	(.107)	(.011)
Constant	.109***	.090***
	(.037)	(.044)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	62,372	65,458

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratios (column 1) and coefficients (column 2), standard errors, and significance levels from the logistic (column 1) and linear (column 2) regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 Reviewerinlendinggroup_{i,c} + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b submitted a claim, $Reviewerinlendinggroup_{i,c}$ is an indicator equal to 1 if individual i is in the joint liability group of her credit center's, c, claims reviewer, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 11: Effect of informal financial ties on claims decision

	Isaac claim accepted	Sandy claim accepted
Reviewer in lending group remaining on date of hurricane	-.021	.003
	(.012)	(.010)
Years a borrower	-.037* .	-.022
	(.021)	(.014)
Constant	1.148***	1.087***
	(.084)	(.054)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	9,514	14,213

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratios (column 1) and coefficients (column 2), standard errors, and significance levels from the logistic (column 1) and linear (column 2) regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 Reviewerinlendinggroup_{i,c} + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b had an accepted claim, $Reviewerinlendinggroup_{i,c}$ is an indicator equal to 1 if individual i is in the joint liability group of her credit center's, c, claims reviewer, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 12: Effect of informal financial ties $\times$ loan period remaining on claims submission

	Borrower submitted claim (OR)	Borrower submitted claim (linear)
Percentage of borrower's loan period remaining	1.067	.009
	(.242)	(.028)
Reviewer in lending group	1.367**	.046**
	(.292)	(.019)
Reviewer in lending group X Percentage of borrower's loan period remaining	1.151	.016
	(.293)	(.031)
Years a client	1.179	.021
	(.139)	(.014)
Constant	.241***	.236***
	(.110)	(.056)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	49,210	51,422

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratios (column 1) and coefficients (column 2), standard errors, and significance levels from the logistic (column 1) and linear (column 2) regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 Reviewerinlendinggroup_i + \alpha_3 Reviewerinlendinggroup_{i,c} \times LoanCycleRemaining_i + \alpha_4 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b submitted a claim, $Reviewerinlendinggroup_i, c$ is an indicator equal to 1 if individual i is in the joint liability group of her credit center's, c, claims reviewer, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 13: Effect of insurance benefit on joint liability group switches

	Ever switched group (OR)	Number of distinct groups (linear)
Percent of borrower's loan period remaining on date of hurricane	2.597***	.221***
	(.365)	(.031)
Years a borrower	1.274***	.047***
	(.113)	(.017)
Constant	1.94	2.01***
	(2.601)	(.113)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	15,004	15,004

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports odds-ratios (column 1) and coefficients (column 2), standard errors, and significance levels from the logistic (column 1) and linear (column 2) regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where in Column 1 $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b switches joint liability groups at least one time over the subsequent three years and in Column 2 $y_{i,c,l,b}$ is the count of distinct joint liability groups individual i belongs to over the subsequent three years, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level. The sample is restricted to only those individuals who continue as active borrowers three years later.

Table 14: Effect of insurance benefit on the intensive margin: loan size and savings

	Two years later		Three years later	
	Loan amount (HTG)	Savings amount (HTG)	Loan amount (HTG)	Savings amount (HTG)
Percent of borrower's loan period remaining on date of hurricane	-352***	-740*	-183	-679
	(138)	(436)	(166)	(574)
Years a borrower	941***	4506***	1119***	4588***
	(76)	(245)	(106)	(325)
Constant	890	-5524***	1523***	-2854*
	(767)	(1042)	(444)	(1668)
Branch FE	Yes	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes	Yes
Observations	14,993	15,004	10,213	10,214

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the linear regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where the dependent variable $y_{i,c,l,b}$ is loan size (column 1 and 3) and savings account balance (column 2 and 4) for individual i in credit center c with loan officer l at bank branch b defaulted over the subsequent two (column 1 and 2) and three (column 3 and 4) years, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level. Note: 40 HTG = 1 USD in 2012, approximately.

Table 15: Effect of insurance benefit on the intensive margin: delinquencies and days late

	Two years later		Three years later	
	Delinquent (OR)	Days late	Delinquent (OR)	Days late
Percent of borrower's loan period remaining on date of hurricane	1.39***	23.251**	1.69**	10.773*
	(.199)	(9.62)	(.385)	(5.548)
Years a borrower	.949	-11.474*	.991	-1.499
	(.088)	(6.506)	(.134)	(2.918)
Constant	14.069***	279.351***	.314	81.907
	(7.11)	(26.389)	(.335)	(56.189)
Branch FE	Yes	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes	Yes
Observations	14,993	15,004	10,213	10,214

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the logistic (column 1 and 3) and linear (column 2 and 4) regression $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where the dependent variable $y_{i,c,l,b}$ is a binary variable equal to 1 if individual i in credit center c with loan officer l at bank branch b was late in repaying any loan by 90 or more days over the subsequent two (column 1) and three (column 3) years, or $y_{i,c,l,b}$ is the max number of days late individual i in credit center c with loan officer l at bank branch b was on any loan repayment over the subsequent two (column 2) and three (column 4) years, respectively, $LoanCycleRemaining_i$ is the percent of borrower i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a borrower of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 16: Effects of weather exposure on demand for credit

	Hurricane Isaac		Hurricane Sandy	
	Active two years later	Active three years later	Active two years later	Active three years later
Rainfall	.000	.000	.000	.000
	(.001)	(.000)	(.001)	(.000)
Wind	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)
Flood	.041	.048**	.010	.019**
	(.027)	(.023)	(.011)	(.009)
Branch FE	Yes	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes	Yes
Observations	23,604	23,604	23,604	23,604

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the linear regression $y_{i,c,l,b} = \kappa_1 + \kappa_2 WeatherExposure_c + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where the dependent variable $y_{i,c,l,b}$ is a binary variable equal to 1 if individual i in credit center c with loan officer l at bank branch b remains an active borrower over the subsequent two (column 1 and 3) and three (column 2 and 4) years, $WeatherExposure_c$ is exposure to rainfall, wind, or flood in Hurricane Isaac (column 1 and 2) or Sandy (column 3 and 4), γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 17: Ruling out confounding from informal financial proximity

	Reviewer in lending group (OR)	Borrower active 2014 (OR)	Borrower active 2014 (OR)
Percentage of borrower's loan period remaining	.997	2.237***	2.338***
	(.136)	(.234)	(.251)
Reviewer in lending group	–	. 1.136**	1.329**
		(.071)	(.160)
Reviewer in lending group × Percentage of borrower's loan period remaining	–	–	.703
			(.159)
Years a borrower	1.469***	.934	.934
	(.135)	(.070)	(.071)
Constant	.050	1.043***	1.021***
	(.053)	(.570)	(.565)
Branch FE	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes
Observations	21,321	21,321	21,321

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column 1 of this table reports odds-ratios, standard errors, and significance levels from the logistic regression $InformalTies_{i,c,l,b} = \beta_1 + \beta_2 LoanCycleRemaining_i + \beta_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where the dependent variable $InformalTies_{i,c,l,b}$ is a binary variable equal to 1 if individual i in credit center c with loan officer l at bank branch b is in the joint liability group of the peer reviewer of her credit center c. Columns 2 and 3 report odds-ratios, standard errors, and significance levels from the logistic regressions $y_{i,c,l,b} = \beta_1 + \beta_2 LoanCycleRemaining_i + \beta_3 InformalTies_{i,c,l,b} + \beta_4 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, and $y_{i,c,l,b} = \beta_1 + \beta_2 LoanCycleRemaining_i + \beta_3 InformalTies_{i,c} + \beta_4 LoanCycleRemaining_i \times InformalTies_{i,c} \beta_5 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$ where the dependent variable $y_{i,c,l,b}$ is a dummy variable equal to 1 if borrower i is active two years later.

Table 18: Results of placebo tests (linear regressions)

	Borrower active 2014	Borrower active 2015	Defaults	Ever switched group (logistic)	Number of switches (linear)
Percentage of borrower's loan	.048***	.019*	.007	.008	.014
period remaining	(.012)	(.011)	(.010)	(.011)	(.013)
Years a borrower	.003	.035**	.020**	.020**	.025
	(.013)	(.014)	.008	(.012)	(.015)
Constant	.427***	.259***	.018**	.410***	1.44***
	(.055)	(.057)	(.033)	(.048)	(.059)
Branch FE	Yes	Yes	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes	Yes	Yes
Observations	31,561	31,561	31,561	31,561	31,561

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from following regression using the "placebo cohort", the subsample of individuals with active loans during the hurricanes who made no claim: $y_{i,c,l,b} = \alpha_1 + \alpha_2 LoanCycleRemaining_i + \alpha_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b has an active loan two years later (column 1), three years later (column 2), a dummy variable equal to 1 if individual i defaulted on a subsequent loan (column 3), a dummy variable equal to 1 if individual i switched joint liability groups at least one time over the subsequent three years (column 4), and the count of distinct joint liability groups individual i belonged to over the subsequent three years (column 5); where $LoanCycleRemaining_i$ is the percent of individual i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a individual of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 19: Effect of insurance benefits on demand for credit: exploiting variation in instrument $\times$ using the placebo cohort as a control group

	Borrower active 2014	Borrower active 2015
Percentage of borrower's loan	.047***	.019*
period remaining (e.g. percent of loan forgiven)	(.012)	(.011)
Borrower made claim	.034**	.029**
	(.017)	(.013)
Borrower made claim $\times$ Percentage	.109***	.061***
of borrower's loan period remaining	(.024)	(.019)
Years a borrower	.003	.033**
	(.014)	(.014)
Constant	.423***	.225***
	(.055)	(.057)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	53,150	53,150

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the regression specification $y_{i,c,l,b} = \delta_1 + \delta_2 MadeClaim_i + \delta_3 LoanCycleRemaining_i + \delta_4 MadeClaim_i \times LoanCycleRemaining_i + \alpha_5 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b has an active loan two years later (column 1) or three years later (column 2), $MadeClaim_i$ equals 1 if individual i made an insurance claim for Hurricane Isaac and/or Sandy, $LoanCycleRemaining_i$ is the percent of individual i's loan period remaining on date of the hurricane, $years_i$ are the number of years individual i has been a individual of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Table 20: Restricting sample to span of time just before a loan started or just after loan cycle ended

	Borrower active 2014	Borrower active 2015
Eighty percent or more of loan period forgiven	.142***	.070***
	(.024)	(.025)
Years a borrower	-.020	.009
	(.025)	(.025)
Constant	.592***	.220**
	(.143)	(.110)
Branch FE	Yes	Yes
Loan officer FE	Yes	Yes
Observations	6,333	6,333

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients, standard errors, and significance levels from the following regression, whehn restricing the sample to only those individuals with $LoanCycleRemaining_i \leq .20$ or $LoanCycleRemaining_i \geq .80$: $y_{i,c,l,b} = \alpha_1 + \alpha_2 EightyPercent_i + \beta_3 years_i + \gamma_b + \gamma_l + \varepsilon_{i,c}$, where $y_{i,c,l,b}$ is a binary indicator equal to 1 if individual i in credit center c with loan officer l at bank branch b has an active loan two years later (column 1) or three years later (column 2), $EightyPercent_i$ equals 1 if $LoanCycleRemaining_i \geq .80$, $years_i$ are the number of years individual i has been a individual of the microfinance institution, γ_b are branch level fixed effects, γ_l are loan officer fixed effects, $\varepsilon_{i,c}$ are heteroskedasticity-robust standard errors clustered at the credit center level.

Bibliography

Banerjee, Abhijit, Esther Duflo, and Richard Hornbeck (2014). "Bundling health insurance and microfinance in India: There cannot be adverse selection if there is no demand." In: *The American economic review* 104.5, p. 291.

Banerjee, Abhijit et al. (2013). "The diffusion of microfinance." In: *Science* 341.6144, p. 1236498.

Banerjee, Abhijit et al. (2015). "Do credit constraints limit entrepreneurship? Heterogeneity in the returns to microfinance." In:

Breza, Emily (2012). "Peer effects and loan repayment: Evidence from the krishna default crisis." In: *Job Market Paper MIT*.

— (2015). *Field experiments, social networks, and development*.

Breza, Emily and Arun G Chandrasekhar (2015). *Social networks, reputation and commitment: Evidence from a savings monitors experiment*. Tech. rep. National Bureau of Economic Research.

Breza, Emily, Arun G Chandrasekhar, and Horacio Larreguy (2014). *Social structure and institutional design: evidence from a lab experiment in the field*. Tech. rep. National Bureau of Economic Research.

Cai, Jing et al. (2012). "The impact of insurance provision on households' production and financial decisions." In: *Département d'économie, Université du Michigan*.

Carter, Michael R, Lan Cheng, and Alexander Sarris (2011). "The impact of interlinked index insurance and credit contracts on financial market deepening and small farm productivity." In: *Annual Meeting of the American Applied Economics Association, Pittsburgh PA, July*, pp. 24–26.

Clarke, Daniel J et al. (2011). *Reinsuring the poor: Group microinsurance design and costly state verification*.

Cole, Shawn Allen, Xavier Giné, and James I Vickery (2013). "How does risk management influence production decisions? Evidence from a field experiment." In: *Evidence from a Field Experiment (July 1, 2013). World Bank Policy Research Working Paper* 6546.

Crépon, Bruno et al. (2015). "Estimating the Impact of Microcredit on Those Who Take It Up: Evidence from a Randomized Experiment in Morocco." In: *American Economic Journal: Applied Economics* 7.1, pp. 123–150.

Dercon, Stefan et al. (2014). "Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia." In: *Journal of Development Economics* 106, pp. 132–143.

EM-DAT, CRED (2012). *The International Disaster Database.*

Fonkoze (2014). *Annual Report: Celebrating Twenty Years.* Tech. rep.

Ghatak, Maitreesh (1999). "Group lending, local information and peer selection." In: *Journal of development Economics* 60.1, pp. 27–50.

Ghatak, Maitreesh and Timothy W Guinnane (1999). "The economics of lending with joint liability: theory and practice." In: *Journal of development economics* 60.1, pp. 195–228.

Giné, Xavier and Martin Kanz (2014). "The economic effects of a borrower bailout: evidence from an emerging market." In: *World Bank Policy Research Working Paper* 7109.

Giné, Xavier and Dean Yang (2009). "Insurance, credit, and technology adoption: Field experimental evidencefrom Malawi." In: *Journal of development Economics* 89.1, pp. 1–11.

Guiteras, Raymond, Amir Jina, and A Mushfiq Mobarak (2015). "Satellites, Self-reports, and Submersion: Exposure to Floods in Bangladesh." In: *The American Economic Review* 105.5, pp. 232–236.

Hsiang, Solomon M (2010). "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America." In: *Proceedings of the National Academy of Sciences* 107.35, pp. 15367–15372.

Jolly, Curtis M (1998). "Market Structure of Food Markets in Haiti: Myths and Reality." In: *Journal of Food Products Marketing* 5.1, pp. 67–82.

Kanz, Martin (2014). "What does debt relief do for development? Evidence from a large-scale policy experiment." In:

Karlan, Dean et al. (2014). "Agricultural Decisions after Relaxing Credit and Risk Constraints." In: *The Quarterly Journal of Economics* 129.2, pp. 597–652.

Kast, Felipe, Stephan Meier, and Dina Pomeranz (2012). *Under-savers anonymous: Evidence on self-help groups and peer pressure as a savings commitment device.* Tech. rep. National Bureau of Economic Research.

Mobarak, Ahmed Mushfiq and Mark R Rosenzweig (2013). "Informal risk sharing, index insurance, and risk taking in developing countries." In: *The American Economic Review* 103.3, pp. 375–380.

N'Zengou-Tayo, Marie-José (1998). "'Fanm se poto mitan: Haitian woman, the pillar of society." In: *Feminist review* 59.1, pp. 118–142.

Rhodes, Leara (2001). "Haitian heroines." In: *The International Economy* 15.6, p. 38.

Tappendorf, Tyler (2012). *Evaluation of First Year Results of Fonkoze's Kore W Natural Catastrophe Insurance for Haitian Micro-Entrepreneurs.* Tech. rep.

Zinman, Jonathan (2015). "Household Debt: Facts, Puzzles, Theories, and Policies." In: *economics* 7.1, pp. 251–276.