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Bank Strategies in Catastrophe Settings: Empirical Evidence and Policy Suggestions

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Abstract

The poor in developing countries are the most exposed to natural catastrophes and microfinance organizations may potentially ease their economic recovery. Yet, no evidence on MFIs strategies after natural disasters exists. We aim to fill this gap by building adataset which merges bank records of loans, issued before and after the 2004 Tsunami by a Sri Lankan MFI recapitalized by Western donors, with detailed survey data on the corresponding borrowers. Evidence of effective post-calamity intervention is supported since the defaults in the post-Tsunami years (2004-2006) do not imply smaller loans in the period following the recovery (2007-2011) while people hit by the calamity receive more money. Furthermore, a cross-subsidization mechanism is in place: clients with a long successful credit history and those not damaged by the calamity pay higher interest rates. All these features helped damaged people to recover and repay both new and previous loans. However, we also document an abnormal and significant increase in default rates of non victims suggesting the existence of contagion and/or strategic default problems. For this reason we suggest reconversion of donor aid into financial support to compulsory microinsurance schemes for borrowers.

Keywords: Tsunami, disaster recovery, microfinance, strategic default, contagion, microinsurance.

JEL codes: G21, G32, G33.

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Table of contents

1. Introduction

2. The database

3. Descriptive statistics and balancing properties

4. Econometric results

4.1 Determinants of loan amounts

4.2 The determinants of credit defaults

4.3 Further evidence on the contagion/strategic default hypothesis

5. Ex-ante coping strategies and the need for microinsurance schemes

6. Conclusions

References

1. Introduction

Natural catastrophes cause economic destruction and have severe consequences on household income, assets, welfare and nutrition. Over the last decades the variability as well as the frequency and strength of climate-related extremes have increased alarmingly. There are several reasons for this upward trend, the most relevant ones being human-driven climate changes and land misuse which have increased the number and severity of some type of disasters like hurricanes and floods. As it is well known, low and middle income countries suffer the most from these events due to unfavorable weather conditions, high population density, poor quality of buildings and infrastructures, lower insurance protection and, more in general, lower financial resources required to cope with them (Cummins and Mahul, 2009). These catastrophic events bring the economic system to an halt in a similar way to a heart attack. In order to restore financial and economic flows what is needed is a shock therapy (a defibrillator) which soon restores liquidity of the system. This is why in this dramatic scenario several authors have tested whether (survival and/or recapitalization of) microfinance institutions may help to compensate the losses and recover from natural catastrophes and investigated how the same local credit intermediaries - which are crucial to restore liquidity - may survive to the shock.

In this respect, many studies document that support from MFIs can be scarce if their loan portfolios end up being severely damaged by the catastrophe, in which case the survival of the whole bank serving the poor can be at risk. Collier et al. (2011), using portfolio-level monthly data of a Peruvian MFI from January 1994 to October 2008, show that the 1997-1998 El Niño significantly increased loan problems. This is because after a natural disaster a contemporaneous increase in the demand and a fall in the supply of credit - the latter due to an increase in bad loans - can generate a significant and long-lasting disequilibrium. Evidence of mismatches between demand and supply of credit after a natural catastrophe has been provided by Berg and Schrader (2009) who analyze the effect of volcanic eruptions in Ecuador on the demand for loans and access to credit. The authors show that, while the former increased due to volcanic activity, the latter was restricted for new clients.

On the positive side Khandker (2007) documents with household-level panel data that the 1998 flood in Bangladesh increased vulnerability to poverty reducing both consumption and assets while microfinance helped to compensate the losses from the flood. In a sample of South-Western Sri Lankan borrowers Becchetti and Castriota (2010 and 2011) find that the 2004 Tsunami caused significant economic and psychological losses and document that MFI recapitalization helped to recover pre-Tsunami welfare levels and achieve convergence with non-damaged individuals. De Melo ert al. (2012) obtain similar results in the same geographical context, showing that a lack of access to capital inhibits the recovery process and that firms receiving randomly allocated grants recover profit levels almost two years before other damaged firms. [1]

Note, however, that during catastrophes credit mechanisms can worsen also due to strategic defaults and contagion and MFIs may be particularly vulnerable to these

[1] The studies by Becchetti and Castriota (2010 and 2011) and De Melo et al. (2012) are similar with respect to the scope of the investigation, the period of data collection and the geographical context (three villages in South Western Sri Lanka, Galle and Matara being in common), but use two different methodologies. In fact, Becchetti et al. (2010 and 2011) adopted the Retrospective Analysis of Fundamental Events Contiguous to Treatment (RETRAFECT) methodology used by McIntosh et al. (2011) which borrows from event studies used in the finance literature. This methodology relies on a single cross-sectional survey to create a retrospective panel dataset based on fundamental events in the history of households. De Melo et al. (2012), instead, use panel data and randomized experiments.

phenomena in presence of joint liability clauses. This is because under these contractual arrangements the default of one (or more) borrowers hit by the shock increases the burden of solvent groupmates not directly affected by the calamity. Under these circumstances a "domino effect" can therefore lead to the default of the entire group and, eventually, of the whole MFI. Bratton (1986) shows that group lending is better than individual lending in good times, the reverse being true in times of crisis. Evidence of domino effects is provided by Paxton (1996) in Burkina Faso.

As a consequence, if borrowers believe that many clients will default, and that this would eventually lead the MFI to bankruptcy (or to require higher lending rates in the future to survive), they may strategically decide to default since microfinance institutions rely on the promise of future loans to induce repayment. Bond and Rai (2008) refer to such phenomenon as borrowers' run. Evidence in this sense is found in Goering and Marx (1998) in the case of Childreach in Ecuador where the number of defaults multiplied as the word spread that few people were paying back. Similar results are obtained with a different approach by Cassar and Wydick (2010) who carry out group lending experiments in five countries and demonstrate that players have an incentive to verify if they believe that a critical number of other group members will do the same.

Our research aims at studying whether these phenomena are at work after a natural disaster by investigating the determinants of loan amounts and credit defaults in a Sri Lankan microfinance organization severely damaged by the 2004 Tsunami and recapitalized by Western donors after it. In our empirical investigation we rely on a broad range of controls which provide insights into the credit mechanisms of the institution and the clients' repayment incentives. The focus is on the effects of the Tsunami on the MFI's operating principles and on the borrowers' insolvency.

Two main results emerge from the empirical analysis. First, standard lending rules, which imply that clients do not obtain new loans until they repay old ones, are suspended in order to help Tsunami victims to recover from the catastrophe. Second, having been damaged by the 2004 Tsunami has no effect on credit defaults, after controlling for other confounding elements like socio-demographic, economic variables, and external support and donations. This finding is paralleled after the calamity (years 2004-2006) by a significant and unexpected increase in default rates of borrowers not affected by the Tsunami and a significant difference in (higher) lending rates paid by non victims *vis à vis* victims in the post-Tsunami period. This higher interest rate is not casual since international organizations and donors explicitly imposed AMF to lend money to the victims at a lower (subsidized) interest rate. This could have induced some borrowers to declare the status of victim in order to obtain loans with better economic conditions.

This evidence suggests that strategic defaults and/or contagion may be in place - although our data do not allow us to disentangle the two phenomena.[2] All these results imply that ex-post external support to MFIs with a relevant share of bad loans helps damaged people to avoid contagion and recover from the calamity, but also generates moral hazard problems for non damaged ones under the assumption of asymmetric information between AMF and the latter. Our policy advice is that the problem could be avoided with the reconversion of donor aid into financial support to

[2] What may be inferred is that, would AMF be able to bridge after the tsunami the asymmetric information with borrowers, the strategic default rationale would be ruled out. We do not have however information which allows us to test this hypothesis.

compulsory (calamity specific) microinsurance schemes attached to the loans. This would prevent borrowers unaffected by future calamities from having negative expectations on their own financial burden and on the MFI future survival, thereby preventing both contagion and strategic default.

The rest of the paper is organized as follows. Section 2 describes how the database has been created. Section 3 provides summary statistics and descriptive evidence of the MFI sample portfolio deterioration after the hazard. Section 4 reports econometric results over the determinants of loan amounts and credit defaults. Section 5 discusses the need of compulsory microinsurance schemes attached to bank loans as a possible solution to moral hazard problems. Section 6 concludes.

2. The database

Our database is created by merging bank records and survey data. It consists of information on 767 loans issued from 1995 to 2011 to 200 randomly sampled clients living in the villages of Galle, Matara and Hambantota by Agro Micro Finance, a Sri Lankan MFI headquartered in the capital Colombo with regional branches in the South-West of the country.

The Tsunami was an unexpected event, therefore it was impossible to organize repeated interviews over time, before and after the catastrophe. For this reason we adopted the Retrospective Analysis of Fundamental Events Contiguous to Treatment (RETRAFECT) methodology used by McIntosh et al. (2011) which borrows from event studies used in the finance literature. This methodology relies on cross-sectional surveys to create a retrospective panel dataset based on fundamental events in the history of households.

We interviewed MFI borrowers twice: the first time in April 2007 and the second in December 2011. Interviews were conducted at the monthly AMF meetings or at the clients' homes and made use of professional translators who received intensive training by the team of researchers and Agro Micro Finance staff members. In April 2007 respondents were asked to declare current and remember past levels of different wellbeing indicators by making reference to four different periods. We selected periods easy to remember due to the occurrence of memorable events.

The four considered time windows are: (P1) the six month interval before the first microfinance loan ever obtained; (P2) the period going from the first microfinance loan to the tsunami date (26th of December 2004); (P3) the period between the tsunami date and the first microfinance loan after tsunami and (P4) the period from the first microfinance loan after tsunami to the survey date (April 2007). In December 2011 we updated the project, which allowed us to collect additional information for a fifth window (P5) consisting of the six months preceding the interview. Figure 1 shows the time schedule of the two surveys and the five reconstructed windows. A first step of the research consisted in merging bank and survey data: in this way when studying the determinants of credit defaults we are able to provide, for each of the 767 loans released by the MFI, a number of additional controls.[3]

[3] In the estimates which follow the retrospective approach is used only to calculate income while all other data come from official bank files. Our results are robust to the omission of the income variable and therefore hold also when not using the retrospective approach. Evidence is omitted for reasons of space and available upon request.

More specifically, our records provide official bank information on loan characteristics such as initial and end dates, duration, amount released, interest rate charged, whether the loan has been repaid, and the number of previous loans and of previous defaults. As a complement, the two surveys allow us to collect information on socio-demographic and economic variables, the damages suffered from the Tsunami, and the support received after the calamity from family members, friends, the Government and other organizations. This information is important since it can affect the demand for loans and the default rates.

Another fundamental variable which could influence the two variables of interest is the initial income of the borrower. In fact, institutions achieving financial sustainability could lend higher amounts to wealthier people whose implicit risk is lower, while organizations achieving outreach might privilege poorer clients. Similarly, default rates could be influenced by initial income in that, during difficult times, wealthier people can repay the loan without sacrificing basic needs such as nutrition and children education. Although at a first glance it is normal to believe that income is less memorable than other variables, Becchetti and Castriota (2011) find that it is strongly correlated with memories about average weekly hours of work, problems in providing daily meals to the family and self-declared satisfaction about overall economic situation. Answers about these variables are consistent for all the considered windows. For this reason, when running regressions we include in the specification the income of the previous window.

Given these database characteristics, from a methodological point of view our work has a number of strengths with respect to other articles studying the consequences of the Tsunami on economic and psychological variables (see, for example, Callen, 2009 and Cassar et al., 2011). First, the impact of the hazard is measured at the individual and not at the village level as in many existing works, thereby preventing location bias problems. Second, we do not constrain ourselves to considering only whether the person experienced or not the calamity. In fact, we identify six different types of possible damages and build a proxy for the intensity of the shock. The six types of economic and psychological damages are: i) family members dead or injured; damages to ii) house; iii) office buildings; iv) working tools; v) raw materials; vi) economic activity in , since after the catastrophe the demand for most items collapsed given that financial resources were used to repair the damages. [4]

These original features help to solve the identification problem arising from the impossibility of randomizing ex ante the calamity experience, that is, the causality link from the Tsunami shock to loan preferences. In fact, it could be argued that wealthier and less risky borrowers selected areas (in which they have family, house and economic activities) which were more likely to be inundated by the Tsunami. This could be the case if rich people were willing to pay an extra price for houses with view on the ocean or if the closer distance from the coast implied higher revenues (e.g. coming from profitable businesses like tourism) or lower transportation costs due to better infrastructures and higher population density.

Such interpretation is hardly plausible since: i) damaged and non damaged individuals living in the same villages are very similar with respect to observables (and, arguably, unobservables) (see section 3); ii) people in our sample did not change residence before and after the calamity; iii) the degree of heterogeneity among

[4] Most borrowers were interviewed at home in the 2007 post-tsunami survey. Damages of those interviewed at AMF were checked. Hence we could personally verify that the damage variables were not affected by measurement error.

individuals is minimized by the fact that they are all clients of an MFI and received loans to finance business activities. As a consequence we expect that: i) attendance of entrepreneurship trainings and monthly borrowers meetings shaped a similar economic mentality; ii) interviewed borrowers are similar with respect to some unobservable factors (main suspect of self-selection) like sense of entrepreneurship and trustworthiness which helped them to pass the screening selection of the bank.

Finally, it could be argued that the most severely hit by the natural calamity left their village and migrated somewhere else. Although we do not have official data on migration of clients before and after the Tsunami, the AMF management reports anecdotic evidence in favour of the inexistence of a self-selection bias of the least damaged individuals, the possible incentive to stay being the possibility to receive new loans after the calamity. This option would have been difficult to explore if a person applied for a loan in a new region after having lost all her belongings and without having previous successful track records.

3. Descriptive statistics and balancing properties

Table 1 provides a description of the variables used while Table 2 reports summary statistics. The average loan amount in December 2011 terms is above 66,000 Sri Lankan Rupees (Rps.), which is a considerable amount based on the local living standards. AMF's declared policy, common to many similar institutions, is to start it with smaller loans in order to test the client's ability to repay, increasing over time the amount lent. From this point of view MFIs privilege financial sustainability to outreach since it is reasonable to assume that, at the beginning, when they are starting a new business, clients are more in need of funds but are also riskier. From Table 3 it is possible to observe that, net of the general upward trend over time, the average amounts of loans peaked after the Tsunami because of the combined effect of the increased demand to recover from the damages and bank recapitalization which generated an inflow of financial resources. In our sample 18% of loans have not been repaid: such a high share is due to the unexpected 2004 calamity which caused massive defaults, as shown by the 2005 90% peak in Table 3.

The annualised nominal interest rate is around 37 percent. This rate is not particularly high if we consider the relatively high inflation rate which has ranged between 3 and 23 percent in the period under scrutiny, the small average amount and the relatively short duration of loans which (compared to ordinary banks) boost the administrative expenses and force MFIs to charge high interest rates on loans (especially if we consider infra-annual loans) (Hardly et al., 2003). As shown in Table 3 the average interest rate fluctuates over time according to market conditions, but decreases after the Tsunami because of donors' constraints on the use of the released funds. In fact, damaged people were entitled to receive loans at favorable conditions (6% interest rate).

The duration of the loans ranges from one day (0.03 months) for small amounts to four years for big amounts, for which the authorization of the regional or even central manager is required. The most common frequency schemes are based on monthly, followed by weekly and bi-monthly installments, even though bank managers are free to choose longer or shorter maturities depending on the amounts released, the type of businesses financed, the credit history and the distance from the local branch which affects the monitoring costs. Around 11% of loans have been issued to start a new business (start-up) or launch a new product (spin-off), 82% to finance ongoing businesses and 6% to recover from the natural calamity.

The "source of the initiative" is a relevant aspect of the lender-borrower relationship which is able to influence the average amount of loans issued by a bank and the default rates. The possible "source of initiative" answers in our survey are: (i) AMF (35% of loans in our sample); (ii) the client, following the suggestion of a borrower who introduced him to the bank manager (35%); (iii) the client, spontaneously, without the support of anybody (29%). On the one hand, people who spontaneously look for a loan are likely to be more proactive and enterprising, which is a signal the bank could use to identify the client's profile. On the other hand, individuals who are introduced to AMF by senior clients benefit from "reputation spillovers": new members joining a group "inherit" the good or bad reputation of the coalition, so that collective reputation turns out to be history dependent (Tirole, 1996). Furthermore, they become immediately part of a group of people with more similar characteristics and stronger social ties, which could affect loan amounts and default rates as shown by Cassar et al. (2007) with field experiments in South Africa and Armenia. As a consequence, whether proactive borrowers will obtain more/less money and will have higher/lower default rates is an empirical issue we are going to analyze with econometric regressions in section 4.

The number of previously released and repaid loans ranges from 0 (new clients) to 27, while that of previous defaults from 0 to 2. The average distance from the closest AMF branch is 15 km, which is non-negligible given the poor quality of road infrastructures and the scarcity of own transportation means. In line with most MFIs, the vast majority of loans have been released to women. Age, education and family size are in line with regional values. Most borrowers are involved in manufacturing and trade, while a relevant share has more than one economic activity (the sum of the mean values of the dummies for the types of activity exceeds one). The average real monthly income in 2011 terms of the time window preceding the loan was around 34,000 Rps., ranging from 0 in the aftermath of the Tsunami for those severely hit by the wave to a maximum of 132,000 Rps. for successful entrepreneurs.

Around half (47%) of loans have been released to people damaged by the Tsunami, the number of damage types ranging from 0 to 6. Among the six types considered the first five refer to the direct shock caused by the calamity while the last one (damage to the economic activity) is indirect and refers to the decrease in market demand. From Table 2c it emerges that indirect effects are the most common (39%), followed by damages to raw materials (24%), working tools (18%), office buildings (17%) and house (11%), while those on family members are rare (1%). Note that the dummy variables for the damages and *Sum of Damages* are obviously zero for all loans released before the Tsunami event.

With respect to external support, only 2% of loans have been provided to people receiving remittances from abroad, donations and subsidies being more frequent (respectively 5% and 11%). Finally, while loans provided by other MFIs and other people are extremely rare (1%), those provided by banks and family members or friends are more frequent (respectively 14% and 11%).

Table 4 shows parametric tests for difference in means in terms of loans/borrower characteristics between damaged and non damaged before the Tsunami (P1 and P2). This is meant to test whether characteristics of the loans or those of the borrowers were significantly different and could drive (and bias) the econometric results of section 4. Note that all these variables are either time invariant or verified as being invariant before and after tsunami and therefore their values may be considered as pre-tsunami levels. Our tests document that the null of no difference in observable characteristics between the two groups is never rejected at 5% level (t-stats are always below 1.96).

The respect of balancing properties is likely to be due to the characteristics of our data. As discussed in the introduction our database is composed of people from the same villages living at a close distance from each other and all being members of the same MFI. Participation to one of the two (damaged/undamaged) groups is therefore likely to be due to casual factors such as natural barriers or small differences in distance from the coast.

4. Econometric results

4.1 Determinants of loan amounts

We start our empirical analysis by studying the determinants of loan size in our sample. The estimated specification is:

$$LS_i = \alpha_0 + \alpha_1 Damaged_{it} + \sum_i \beta_i X_{it} + \sum_t \gamma_t \, DYear_t + \sum_j \delta_j Dvillage_j + \varepsilon_i \qquad (1)$$

The dependent variable (LS) is the loan size expressed in December 2011 terms and extracted from the AMF electronic database, while *Damaged* is a unit dummy for borrowers hit by the Tsunami (always equal to zero before the catastrophe) which is introduced in the third specification (Table 5, column 3). Alternatively in column 4 the dummy is replaced by six dummies related to the type of damage suffered and, in column 5, by the sum of damages. The X socio-demographic variables control for gender discrimination, role of seniority and education, household size, business of activity, initial income (of the time window preceding the loan), damages suffered from the Tsunami and external support received. Regressions include village and time dummy variables (*DYear* and *DVillage*) (results on these dummies are omitted for reasons of space but are available upon request). Standard errors are clustered at the borrower level and reported in parentheses[5].

A first main finding is that people hit by the Tsunami (column 3, variable *Damaged*) receive more funds, the relevant type of damage being the indirect one to the economic activity (column 4, *Damage: economic activity*), while the index we built to measure the intensity of the damage (column 5, *Sum of Damages*) does not seem an effective proxy to capture the consequences of the calamity. The economic support AMF received from donors and international organizations was partly conditioned to the Tsunami victims being financed first, therefore the larger amounts lent to victims are not unexpected.

However, it appears that AMF did not lend more to those suffering the most since direct damages (Table 5, column 4) and intensity of the damages (Table 5, column 5) are not significant. Turning to financial variables, while AMF clearly states its policy of lending smaller amounts to new clients and larger amounts to solvent borrowers, econometric results show that the number of previous loans is irrelevant for the amount released. This behavior does not closely correspond to patterns observed in

[5] As a robustness check we run the same regressions without the income of the previous time window and obtain almost identical outcomes. Results are omitted for reasons of space but are available upon request.

microfinance markets where new clients are offered small loans to test their repayment behavior (Vogelgesang, 2003).

An apparently counterintuitive result is the positive effect of previous defaults on the amount released by the bank. Ordinary banks and MFIs most often explicitly forbid to lend money to borrowers until they repay back the amount due. Even if the money is finally repaid, MFIs generally use this piece of information to update the risk profile of the borrower. As a consequence, the coefficient attached to past defaults should be at least non-positive. The reason for this unexpected result is the Tsunami catastrophe which caused serious damages to the businesses and the properties of historically reliable clients (in our sample there are no defaults until the calamity occurred). Without further loans clients would have likely been unable to recover and, in turn, repay the previous loan[6].

The purpose for which the loan has been asked matters. Even though when starting a new business entrepreneurs need more financial resources, lending for a new business is perceived as riskier by the bank which provides smaller loans. In this case AMF seems to behave like traditional bank in that it privileges financial sustainability to outreach.

With respect to the "source of initiative", individuals who are introduced to AMF by another client receive the most, meaning that social ties and reputational spillovers are in place, followed by those who autonomously contact the MFI. Those who get a credit offer on the initiative of the bank receive the least since are less proactive and do not belong to well established and homogenous groups. A growing body of literature

[6] Given the dramatic event, AMF's strategy is in contrast with policies adopted by other MFIs (and by the same AMF before the Tsunami) in more normal contexts like Caja Los Andes in Bolivia which does not provide new grants if a client has not repaid previous loans, as documented by Vogelgesang (2003).

has proved the relevance of social networks in household decision-making (Conley and Udry, 2010) and of personal relationships in credit access, particularly in developing countries (Okten and Osili, 2004). In line with these intuitions Wydick et al. (2011), using survey of 465 households living in Western Guatemala, show that access to credit is closely related to membership of a church network. Our results add to Wydick et al. (2011) in that they study the determinants of access to credit, while our sample is entirely composed by clients and the dependent variable is the loan amount. Social ties not only increase access to credit through imitation phenomena as shown by Wydick et al. (2011), but also increase the average amount of loans through reputational spillovers.

The distance from the MFI branch does not have any significant effect. This might be due to two counteracting forces: on the one hand, closer distance may allow better selection and monitoring of clients while, on the other, due to higher transaction costs (see Ashraf et al., 2006), lending to clients living farther away could be convenient only for larger amounts. Either the two effects cancel out or are not at work.

When looking at the significance of other regressors, the negative coefficient attached to the female gender is surprising since microcredit was born to serve the poor, especially women. It is difficult to say whether such finding depends on discrimination or on unobservable gendered differences in financed project characteristics (i.e. women asking more consumption or small scale loans). Education has a positive effect on loan amounts, meaning that the bank may interpret it as a signal of lower risk profile. It is also likely that more educated people set more advanced, sophisticated and expensive businesses for which a higher amount of money is necessary. The remaining socio-demographic variables are not significant at conventional levels. Initial income does not play any role: the MFI does not lend more neither to poorer nor to richer clients, therefore displaying a policy which tries to balance financial sustainability and outreach. External support in the form of subsidies, donations, remittances and other loans could have reduced in principle the need of credit, but in our regressions do not have any impact on the variable under scrutiny.

4.2 The determinants of credit defaults

In Table 6 we report findings on the determinants of credit defaults based on the following specification

$$Default_i = \alpha_0 + \alpha_1 Damage_{it} + \sum_i \beta_i X_{it} + \sum_t \gamma_t\, DYear_t + \sum_j \delta_j Dvillage_j + \varepsilon_i \quad (2)$$

where the dependent variable (*Default*) is a dummy equal to one if the loan has not been reimbursed, zero otherwise and the other variables are defined as in (Regression 1). Given the discrete nature of the dependent variable the natural candidate for this type of investigation is a Logit model. Again, standard errors are clustered at the borrower level and reported in parentheses[7].

The most interesting result is that the probability of default is neither affected by the Tsunami victim status nor by the intensity of the damages. This finding must imply on the descriptive side a significant increase in the default rate also of non victims in the Tsunami vis à vis the pre-Tsunami period in order to make the victim/non victim effect not significant. This is indeed what we find. Before the Tsunami the default rate of victims and non victims is respectively around 23 and 21 percent and not

[7] As a robustness check we run the same regressions without the income of the previous time window and obtain almost identical outcomes. Results are omitted for reasons of space but are available upon request.

significantly different between the two groups (consistently with balancing properties shown in section 3.2). In the Tsunami period (2004-06) the default rate of victims and non victims raises to 58 and 50 percent, the difference being not statistically different here as well. This result is unexpected, since the Tsunami should not affect positively the probability of default of an individual declaring neither direct (e.g. building and relatives) nor indirect ((economic activity) damages.

We identified two possible explanations for this anomaly: strategic defaults and contagion. With respect to the first hypothesis it might be the case that, as for Childreach in Ecuador (Goering and Marx, 1998), the word spread that few people were paying back the money and that AMF was going bankrupt. Furthermore, donors imposed AMF to lend money to damaged people at a lower and subsidized interest rate, therefore creating an incentive to declare the status of victim. Another - not mutually exclusive - explanation is contagion, since during a hard time of local economic downturn the default of one or two members could have led to the insolvency of the entire group under group lending with joint liability. Contagion problems could have been particularly serious in the light of the restricted size of the groups formed by AMF (minimum three members), which, on the one side, facilitates the creation and the management of groups with similar characteristics, but, on the other, increases the burden for the remaining members in bad times.

When inspecting other financial regressors we find that the interest rate is negatively correlated with default. Abbink et al. (2006) with laboratory experiments find that, on the one side, a higher repayment burden intensifies the incentives to free-ride since shirking allows to save money, but, on the other side, it implies a disciplining effect given that high-interest loans are less tolerant towards defaulters. Cull et al. (2007), using data from 124 institutions in 49 countries, compare group-based versus individual based microfinance institutions and show that, above a certain threshold, interest rates worsen the quality of portfolio in case of individual loans, but this relation does not exist for group-based microfinance institutions. Our results differ from those mentioned above since after the Tsunami (years 2004-2006) AMF carried out a cross-subsidization strategy which consisted of increasing the interest rate to solvent clients in order to reduce it to bankrupt ones[8].

Longer maturities reduce default rates, but the frequency of repayments does not matter. Armendariz and Morduch (2005) with anecdotal evidence from Bangladeshi microfinance providers and McIntosh (2008) with more formal analysis of microfinance contracts offered by FINCA in Uganda find that higher frequency of repayments is associated with lower default rates. However, this could be due to self-selection since clients chose their repayment schedule. Field and Pande (2008) use data from a field experiment with randomized client assignment to a weekly or monthly repayment schedule and find no significant effect of type of repayment schedule on client delinquency or default. Our results are consistent with theirs.

In line with expectations, larger loans imply higher default rates. Credit history does not matter: neither the number of repaid loans nor that of defaults are predictors of current insolvency. This finding is important since it shows that natural calamities can lead people to bankruptcy, but do not generate repeated defaults. In other words, if borrowers receive new support the discontinuity is only temporary and not

[8] Table A1 in the Appendix shows the determinants of the interest rate applied by AMF to each loan: the main drivers of the cost of capital are the client's distance from the local branch, the amount released, the duration and the number of successfully repaid loans. Previous defaults do not lead to an increase in the interest rate.

permanent. Next, while the nature of the credit initiative affects the amount released by the bank, this is not the case for the default rates.

The distance from the closest AMF branch has no effect on default rates: either closer distance does not imply better clients' selection and stricter monitoring[9] or, on the opposite, the selection was so effective that closer and farther clients ended up being homogeneous with respect to the risk profile: this point is left to future research. Finally, the default rate of loans issued to finance start-ups, established business or recovery are the same. Start-ups may show similar mortality rates to other businesses because of contextual factors - small businesses in a growing developing country - which provide consumers' demand and reduce the minimum efficient size of the firm.

With respect to the significance of the remaining regressors we document that socio-demographic controls do not matter. Gender, age, education and number of house members have no effect on repayment rates. Age - a proxy for work experience and wealth - has a negative but not significant effect. Household size could have had a negative effect due to the large family "fixed costs" during calamities and economic downturns, but also a positive one due to the available and free workforce. Either none or both effects are at work here, the final result being null. Past income does not help reducing default risk: this is probably so because, on the one hand, higher income allows more savings, but, on the other, it is a proxy for larger activities which are less flexible on the costs side when the business climate worsens.

[9] Distance among members of the same group has been shown to affect peer monitoring and, in turn, repayment rates (Wydick, 1999). The same principle could have, but does not, work for the borrower-lender relationship.

4.3 Further evidence on the contagion/strategic default hypothesis

To elaborate more around our contagion/strategic default hypothesis we look at determinants of defaults for the control group of non damaged only (Table 7) and find a positive and significant effect of the dummy picking up the post-Tsunami period. Hence, even though non damaged do not declare any consequence from the calamity (including the indirect effect of a demand reduction), they suffer an unexpected increase in default rates in such period. Hence the jump in default rates documented with descriptive findings in section 4.2 is confirmed after controlling for confounding factors in econometric estimates.

A second interesting piece of evidence is the comparison of interest rates between damaged and non damaged in the post-tsunami period. What we find is that the non damaged pay 8 percent more and the difference is significant (p-value 0.002). The consequence of this finding is that non damaged which are groupmates of damaged members have a clear cost in not declaring default, that is, they pay a higher interest rate and, due to the joint liability clause, they may be asked to contribute to pay the loan of their unsolved groupmates hit by the Tsunami. The cost of not declaring strategic default may be a rationale to explain the unexpected increase in default for non damaged in the post tsunami period.

In our database we do not have information on dropouts and therefore the suspicion that our findings may be affected by survivorship bias may arise. Survivorship is generally not balanced between "good" and "bad" borrowers and it may therefore generate a bias via exclusion of a higher share of bankrupt than successful borrowers from the sample. In such case, with reference to our main two dependent variables, it would bias downward *overall sample* default rates while the effect on lending rates would be uncertain (or it may be assumed to generate an upward bias since we found that cross-subsidisation from good borrowers is at stake). Note however that it is reasonable to assume that, if the bias exists, it affects in the same way damaged and non damaged in the pre-tsunami period (damaged and non damaged have not significantly different characteristics ex ante) thereby not altering our main results on the insignificant impact of damaged status on post tsunami defaults. Moreover, in our specific case we verified that AMF lends also to clients who have a record of past default and this minimizes the number of dropouts due to misperformance.

Last, with regard to the post-tsunami period, we know that the support from foreign donors is explicitly targeted to loan concession to borrowers defaulting due to the tsunami. Hence the potential unbalance between damaged and non damaged dropouts after the tsunami is eliminated by such intervention. All this being considered the problem may be considered negligible and not affecting our main findings.

5. Ex-ante coping strategies and the need for microinsurance schemes

Loans provided by MFIs after natural calamities have been proved to be a helpful recovery tool for the victims (Khandker, 2007; Becchetti and Castriota, 2011). Ex-post recapitalization of a struggling MFI with funds provided by donors, NGOs or international organizations is a solution which has been adopted, among others, by the MFI under scrutiny, since neither microinsurance nor contingent repayment schemes were in place at the time of the Tsunami.

However, relying on non automatic but voluntary external fund schemes to recapitalize a deteriorated loan portfolio after calamities is risky for a number of reasons. First, it is not sure whether the institution will find available donors or partners since, when natural catastrophes occur, the number of potential beneficiaries gets large and the competition among them stronger. Second, in case of ex-post (governmental) interventions, budget allocations are often diverted from priority development projects to fund emergency and recovery needs. Third, recapitalizations necessarily occur with a delay, which can worsen the already fragile financial situation of current and potential borrowers looking for new loans.[10] Fourth, because of the delay and of rational/irrational expectations, ex-post solutions do not prevent contagion and/or moral hazard problems connected to strategic defaults as documented in this paper.

Two similar solutions seem appropriate to prevent these two latter phenomena: ex-ante microinsurance schemes attached to loans and contingent repayment systems which allow rescheduling of savings and ex-post installments after natural disasters for affected members. Since 2002 most MFIs in Bangladesh have been introducing this type of scheme (Dowla and Barua, 2006), which in a rural Bangladesh context has been shown to decrease the probability that people skip meals during negative shocks (Shoji, 2009).

However, while the second solution seems adequate in case of natural catastrophes which occur on a more regular basis like floods in Bangladesh, the first seems more effective in case of unpredictable and devastating disasters like the 2004 Asian Tsunami since it does not just postpone, but rather cancel, the outstanding debt. This difference can be of paramount importance when a borrower needs money to recover

[10] As noted by Cummins and Mahul (2009, p.1), "Post-disaster assistance from the international donor community may be slow and unreliable. In the face of the rising frequency and intensity of losses in low- and middle-income countries, the old model of post-disaster financing and reliance on the donor community is increasingly inefficient".

from the catastrophe while the repayment of previous loans prevents the issue of new ones. Furthermore, rescheduling can help to cope with strategic defaults and contagion but does not prevent credit restrictions - especially to new clients. If, instead, a client obtains a new loan without the previous one being canceled, it can be very hard to repay contemporaneously two large sums of money while trying to recover from a natural calamity during a period of economic downturn.

Even though with this dataset we are unable to disentangle the relevance of strategic defaults from that of contagion, a compulsory microinsurance attached to the loans would have prevented both problems and the AMF portfolio deterioration. In fact, it should be kept in mind that in the first quarter of 2005, before receiving foreign support, AMF was technically bankrupt. However, nothing ensures that, if another catastrophe occurred in the future, further external funds from NGOs and other donors would be obtained. This problem is even more severe since AMF clients have experienced international solidarity and refinancing from the bank, therefore they are likely to expect further assistance and support in case of future natural hazards.

6. Conclusions

Very few evidence on the impact of microfinance as post-calamity recovery mechanism exists. We use a unique database made of official bank loans and survey submitted in 2007 and 2011 to evaluate the impact of donors' recapitalization of a Sri Lankan MFI after the Tsunami. Our data show that donors' intervention was effective in supporting victims who received large loans at subsidized rates after their post-Tsunami default. The high default rates among non victim borrowers after the

Tsunami suggest, however, the occurrence of contagion and/or strategic default. This is most likely due to the joint liability clauses of group lending and/or the lower (subsidized) interest rate charged to the Tsunami victims. We suggest that the reconversion of the donors' fund into a compulsory post-calamity insurance for all borrowers may maintain the positive post-intervention effects while solving problems of contagion and strategic default.

Although it is difficult to implement affordable, effective and sustainable catastrophe insurance programs in developing countries, a few successful examples exist, like the Turkish Catastrophe Insurance Pool (TCIP) established with the support of the World Bank after the 2000 Marmare earthquake. The challenge for the future will be to develop, for the highest number of natural calamities and countries, well structured catastrophe insurance markets and, for countries for which potential losses caused by natural disasters are large relative to their national economies or where the cost of mobilizing post-disaster funding is high, an efficient sovereign risk financing (Cummins and Mahul, 2009).

References

[1] Abbink, K., Irlenbusch, B. and Renner, E. (2006), "Interest Rates in Group Lending: a Behavioural Investigation", *Pacific Economic Review*, Vol. 11, No. 2, pp. 185-199.

[2] Armendariz, B. and Morduch, J. (2005), *The Economics of Microfinance,* Cambridge, MA, MIT Press.

[3] Ashraf, N., Karlan, D. and Yin, W. (2006), "Deposit Collectors", *Advances in Economic Analysis & Policy*, Vol. 6, No. 2, pp. 1-22.

[4] Becchetti, L. and Castriota, S. (2010), "The Effects of a Calamity on Income and Wellbeing of Poor Microfinance Borrowers: the Case of the 2004 Tsunami Shock", *Journal of Development Studies*, Vol. 46, No. 2, pp. 211-233.

[5] Becchetti, L. and Castriota, S. (2011), "Does Microfinance Work as a Recovery Tool After Disasters? Evidence from the 2004 Tsunami", *World Development*, Vol. 39, No. 6, pp. 898-912.

[6] Berg, G. and Schrader, J. (2009), "Microcredit, Natural Disasters and Lending", Working Paper.

[7] Blinder, A. S. (1973), "Wage Discrimination: Reduced Form and Structural Estimates", *Journal of Human Resources*, Vol. 8, pp. 436–455.

[8] Bond, P. and Rai, A.S. (2009), "Borrower Runs", *Journal of Development Economics*, Vol. 88, pp. 185-191.

[9] Callen, M. (2009), "Catastrophe and Time Preference: Evidence from the Indian Ocean Earthquake", Working Paper.

[10] Cassar, A., Crowley, L. and Wydick, B. (2007), "The Effects of Social Capital on Group Loan Repayment: Evidence from Field Experiments", *Economic Journal*, Vol. 117, pp. 85-106.

[11] Cassar, A., Healy, A. and von Kessler, K. (2011), "Trust, Risk, and Time Preferences After a Natural Disaster: Experimental Evidence from Thailand", Working Paper.

[12] Cassar, A. and Wydick, B. (2010), "Does Social Capital Matter? Evidence from a Five-Country Group Lending Experiment", *Oxford Economic Papers*, Vol. 62, No. 4, pp. 715-73.

[13] Collier, B., Katchova, A.L. and Skees, J.R. (2011), "Loan Portfolio Performance and El Nino, an Intervention Analysis", *Agricultural Finance Review*, Vol. 71, No. 1, pp. 98-119.

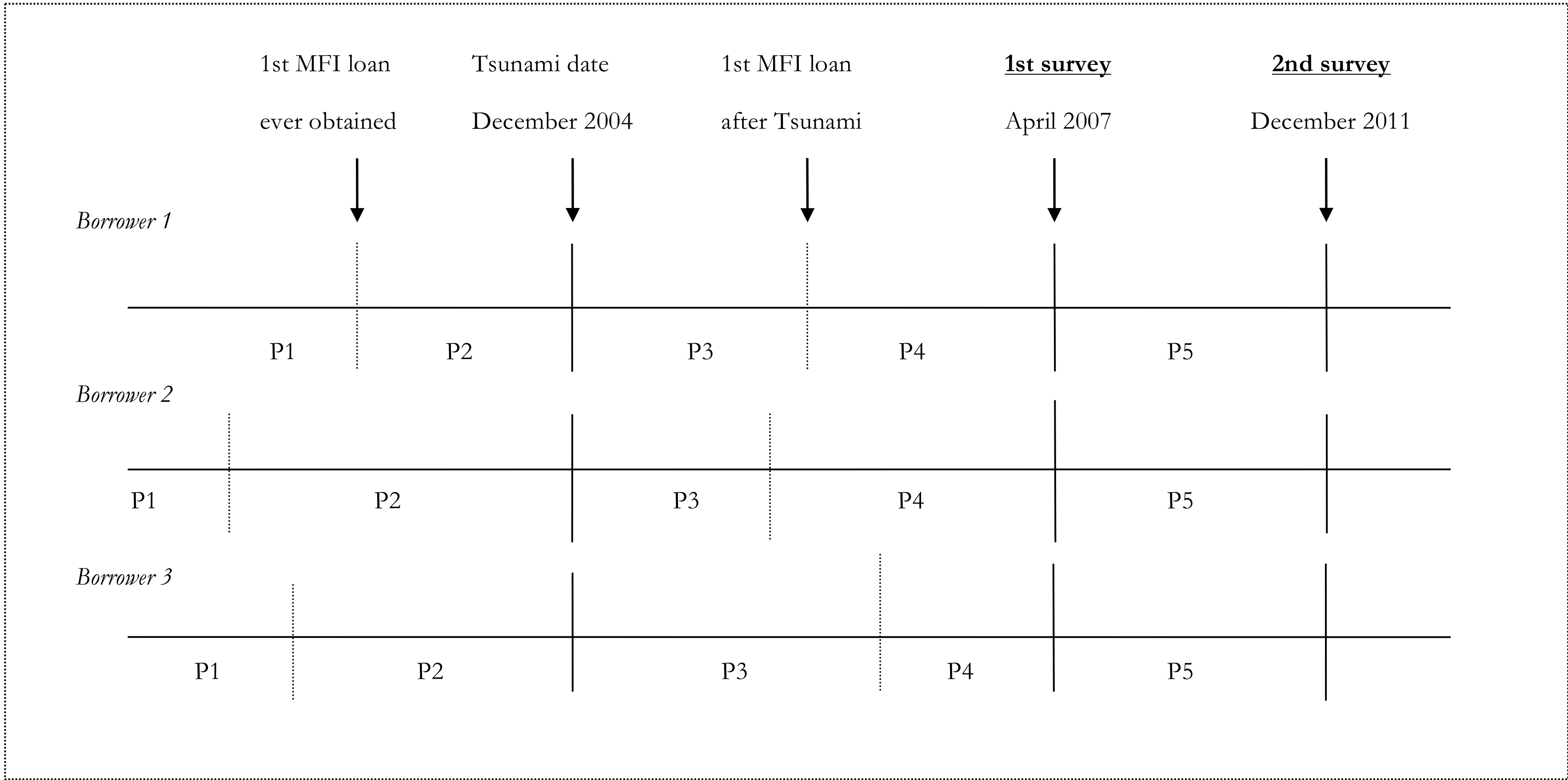
[14] Conley, T. and Udry, C. (2010), "Learning About a New Technology: Pineapple in Ghana", *American Economic Review*, Vol. 100, No. 1, pp. 35-69.

[15] Cull, R., Demirguk-Kunt, A. and Morduch, J. (2007), "Financial Performance and Outreach: a Global Analysis of Leading Microbanks", *Economic Journal*, Vol. 117, p. 107-133.

[16] Cummins, J.D. and Mahul, O. (2009), *Catastrophe Risk Financing in Developing Countries*, available on line at the address:

[16] http://siteresources.worldbank.org/FINANCIALSECTOR/Resources/CATRISKbook.pdf.
[17] De Mel, S., McKenzie, D. and Woodruff, C. (2012), "Enterprise Recovery Following Natural Disasters", *Economic Journal*, Vol. 122, No. 559, pp. 64-91.
[18] Dowla, A. and Barua, D. (2006), *The Poor Always Pay Back*, Bloomfield, CT, Kumarian Press.
[19] Field, E. and Pande, R. (2008), "Repayment Frequency and Default in Micro-Finance: Evidence from India", *Journal of the European Economic Association*, Vol. 6, No. 2-3, pp. 501-509.
[20] Goering, L. and Marx, G. (1998), "Chaos when Credit is Due", *Chicago Tribune*, March 15.
[21] Hardly, D.C., Holden, P. and Prokopenko, V. (2003), "Microfinance Institutions and Public Policy", IMF WP/02/159.
[22] Jann, B. (2008), "The Blinder-Oaxaca Decomposition for Linear Regression Models", *The Stata Journal*, Vol. 8, No. 4, pp. 453-479.
[23] Khandker, S.R. (2007), "Coping with Flood: Role of Institutions in Bangladesh", *Agricultural Economics*, Vol. 36, No. 2, pp. 169-180.
[24] McIntosh, C. (2008), "Estimating Treatment Effects from Spatial Policy Experiments: an Application to Ugandan Microfinance", *Review of Economics and Statistics*, Vol. 90, No. 1, pp. 15-28.
[25] McIntosh, C. Villaran, G. and Wydick, B. (2011), "Microfinance and Home Improvement: Using Retrospective Panel Data to Measure Program Effects on Fundamental Events", *World Development*, Vol. 39, No. 6, pp. 922-937.
[26] Oaxaca, R. (1973), "Male-Female Wage Differentials in Urban Labor Markets", *International Economic Review*, Vol. 14, No. 3, pp. 693-710.
[27] Okten, C. and Osilis, U.O. (2004), "Social Networks and Credit Access in Indonesia", *World Development*, Vol. 32, No. 7, pp. 1225-1246.
[28] Shoji, M. (2009), "Dies Contingent Repayment in Microfinance Help the Poor during Natural Disasters?", *Journal of Development Studies*, Vol. 46, No. 2, pp. 191-210.
[29] Tirole, J. (1996), "A Theory of Collective Reputation", *Review of Economic Studies*, Vol. 63, No. 1, pp. 1-22.
[30] Vogelgesang, U. (2003), "Microfinance in Times of Crisis: The Effects of Competition, Rising Indebtedness, and Economic Crisis on Repayment Behavior", *World Development*, Vol. 31, No. 12, pp. 2085-2114.
[31] Wydick, B. (1999), "Can social cohesion be harnessed to repair market failures? Evidence from group lending in Guatemala", *Economic Journal*, Vol. 109, pp. 463-475.

Figure 1: Time schedule of the two surveys and the five reconstructed time windows



P1= six month interval before first AMF financing.
P2= period ranging from first AMF financing to the tsunami date (December 2004).
P3= period ranging from the tsunami date to the first AMF refinancing.
P4= period ranging from the first AMF refinancing to first the survey date (April 2007).
P5= six month interval before the second survey (December 2011).

Note: Dotted lines indicate non overlapping window borders, continuous lines coincident window borders.

Table 1: Description of the variables used

Table 1a: Financial variables

Loan size	Amount of the AMF loan in December 2011 terms
Default	DV=1 if the loan has not been repaid, 0 otherwise
Interest rate	Annual nominal interest rate on the loan
Duration	Duration of the loan in months
Frequency	Number of installments per month
Reason: new business	DV=1 if the loan has been asked to open a new business, 0 otherwise
Reason: improve	DV=1 if the loan has been asked to improve an existing business, 0 otherwise
Reason: recover	DV=1 if the loan has been asked to recover from the damages, 0 otherwise
Initiative: AMF	DV=1 if , 0 otherwise
Initiative: suggested	DV=1 if , 0 otherwise
Initiative: spontaneously	DV=1 if , 0 otherwise
Previous defaults	Number of previous loans which have not been repaid
Previous repaid loans	Number of previous loans which have been successfully repaid
Distance AMF	Distance from the closest AMF branch in km

Table 1b: Socio-demographic variables

Female	DV=1 if the respondent is female, 0 otherwise
Age	Age of the respondent in years
Education	Education of the respondent in years
House members	Number of people living in the house
Fishery	DV=1 if the respondent is involved in fishery, 0 otherwise
Manufactory	DV=1 if the respondent is involved in manufactory, 0 otherwise
Trade	DV=1 if the respondent is involved in trade, 0 otherwise
Other job	DV=1 if the respondent has another
Real income	Real total household income in December 2011 terms
Matara	DV=1 if the respondent lives in Matara, 0 otherwise
Hambantota	DV=1 if the respondent lives in Hambantota, 0 otherwise
Galle	DV=1 if the respondent lives in Galle, 0 otherwise

Table 1c: Damages from the Tsunami and support received

Damaged	DV=1 if the respondent has been damaged by the Tsunami, 0 otherwise
Damage: family	DV=1 if the respondent reported damages to the family, 0 otherwise
Damage: house	DV=1 if the respondent reported damages to the house, 0 otherwise
Damage: office building	DV=1 if the respondent reported damages to the office building, 0 otherwise
Damage: working tools	DV=1 if the respondent reported damages to the working tools, 0 otherwise
Damage: raw materials	DV=1 if the respondent reported damages to the raw materials, 0 otherwise
Damage: economic activity	DV=1 if the respondent reported damages to the economic activity, 0 otherwise
Sum of damages	Number of types of damage from 0 to 6
Remittances	DV=1 if the respondent receives remittances, 0 otherwise
Subsidies	DV=1 if the respondent receives subsidies, 0 otherwise
Donations and grants	DV=1 if the respondent receives donations and grants, 0 otherwise
Loans: bank	DV=1 if the respondent has obtained other loans from a bank, 0 otherwise
Loans: MFI	DV=1 if the respondent has obtained other loans from another MFI, 0 otherwise
Loans: family/friend	DV=1 if the respondent has obtained other loans from family/friends, 0 otherwise
Loans: other	DV=1 if the respondent has obtained other loans from other people, 0 otherwise

Table 2: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Table 2a: Financial variables					
Loan size	767	66,131	60,629	4,459	324,720
Default	734	0.19	0.39	0	1
Interest rate	767	36.87	23.63	6	101
Duration	765	10.18	7.77	0.03	47.97
Frequency	755	4.12	6.13	0.05	30
Reason: new business	767	0.11	0.32	0	1
Reason: improve	767	0.82	0.39	0	1
Reason: recover	767	0.06	0.24	0	1
Initiative: AMF	733	0.35	0.48	0	1
Initiative: suggested	733	0.35	0.48	0	1
Initiative: spontaneously	733	0.29	0.46	0	1
Previous defaults	767	0.25	0.46	0	2
Previous repaid loans	767	3.23	4.97	0	27
Distance AMF	761	15.16	9.26	0.1	65
Table 2b: Socio-demographic variables					
Female	767	0.88	0.33	0	1
Age	766	47.40	9.58	20	67
Education	757	11.15	2.45	0	16
House members	767	4.45	1.51	1	10
Fishery	761	0.02	0.14	0	1
Manufactory	761	0.38	0.49	0	1
Trade	761	0.40	0.49	0	1
Other job	761	0.14	0.35	0	1
Real income	767	34,213	23,306	0	132,978
Matara	767	0.44	0.50	0	1
Hambantota	767	0.28	0.45	0	1
Galle	767	0.28	0.45	0	1
Table 2c: Damages from the Tsunami and support received					
Damaged	767	0.47	0.50	0	1
Damage: family	767	0.01	0.11	0	1
Damage: house	767	0.11	0.31	0	1
Damage: office building	767	0.17	0.38	0	1
Damage: working tools	767	0.18	0.38	0	1
Damage: raw materials	767	0.24	0.43	0	1
Damage: economic activity	767	0.39	0.49	0	1
Sum of damages	767	1.11	1.55	0	6
Remittances	767	0.02	0.12	0	1
Subsidies	764	0.11	0.31	0	1
Donations and grants	767	0.05	0.22	0	1
Loans: bank	766	0.14	0.35	0	1
Loans: MFI	766	0.01	0.12	0	1
Loans: family/friend	766	0.11	0.32	0	1
Loans: other	760	0.01	0.12	0	1

Table 3: Descriptive statistics of selected variables, by year

Year	Obs.	Loan size	Interest rate	Default (%)
2000	10	32,402	27	0
2001	22	27,157	51	0
2002	39	34,042	40	0
2003	83	36,398	37	0.05
2004	126	37,067	41	0.39
2005	75	59,216	31	0.90
2006	54	109,780	23	0.57
2007	123	82,369	26	0.05
2008	133	84,160	51	0
2009	60	75,143	42	0
2010	22	127,013	19	0
2011	18	97,053	20	0

Table 4: Difference in mean between damaged/non damaged

Variable	Damaged	Non damaged	Difference	T-stat
Table 4a: Financial variables				
Loan size	34,695	32,215	-2,479	-0.56
Default	0.04	0.00	0.04	-1.39
Interest rate	40.51	37.00	-3.51	0.88
Duration	8.62	8.44	-0.18	-0.21
Frequency	4.54	4.04	0.50	-0.34
Reason: new business	0.15	0.09	-0.06	-0.99
Reason: improve	0.85	0.90	0.05	0.87
Reason: recover	0.00	0.00	0.00	N/A
Initiative: AMF	0.35	0.38	0.03	0.37
Initiative: suggested	0.36	0.25	-0.11	-1.24
Initiative: spontaneously	0.28	0.36	0.07	0.88
Previous defaults	0.03	0.00	-0.03	-0.35
Previous repaid loans	0.92	0.88	-0.04	-0.17
Distance AMF	14.48	13.54	-0.94	-0.58
Matara	0.45	0.60	0.15	1.81
Hambantota	0.28	0.16	-0.12	-1.45
Galle	0.26	0.21	-0.05	-0.62
Table 4b: Socio-demographic variables				
Female	0.82	0.86	0.03	0.48
Age	45.01	45.57	0.55	0.34
Education	10.93	11.57	0.63	1.40
House members	4.76	4.30	-0.45	-1.94
Fishery	0.01	0.00	0.01	-0.60
Manufactory	0.38	0.30	-0.07	-0.87
Trade	0.30	0.45	0.14	1.69
Other job	0.16	0.04	-0.11	-1.94
Real income	34,307	36,458	2,151	0.51

Legend: Data refer to the first two time windows (P1 and P2), before the Tsunami.

Table 5: Determinants of loan size

Variables	(1)	(2)	(3)	(4)	(5)
Damaged			25,139***		
			(7,600)		
Damage: family				-5,845	
				(23,313)	
Damage: house				8,094	
				(14,500)	
Damage: office building				3,103	
				(10,436)	
Damage: working tools				-16,532	
				(11,269)	
Damage: raw materials				11,044	
				(11,154)	
Damage: ec. Activity				17,804**	
				(7,343)	
Sum of damages					3,607
					(2,581)
Previous defaults		6,280	6,497	6,875	6,484
		(7,284)	(6,785)	(7,532)	(7,216)
Distance AMF		198.8	218.6	204.8	203.7
		(291.1)	(266.0)	(272.1)	(289.1)
Reason: new business		-12,401	-12,096*	-11,485	-10,352
		(7,910)	(7,069)	(7,244)	(7,662)
Reason: improve		12,408	12,052*	13,358*	14,891*
		(7,941)	(7,110)	(7,448)	(7,853)
Previous repaid loans		-2,433***	-2,911***	-2,850***	-2,535***
		(684.3)	(688.4)	(698.4)	(725.7)
Previous defaults		6,280	6,497	6,875	6,484
		(7,284)	(6,785)	(7,532)	(7,216)
Initiative: suggested		21,077***	19,853***	19,068***	20,233***
		(6,469)	(6,065)	(6,019)	(6,688)
Initiative: spontaneously		14,524**	11,846*	11,821*	13,192*
		(7,219)	(6,926)	(6,701)	(7,328)
Female	-23,358**	-25,966***	-29,013***	-28,200***	-27,187***
	(9,612)	(8,950)	(8,482)	(8,811)	(8,849)
Age	79.47	-27.28	25.85	-48.08	13.95
	(315.8)	(364.0)	(349.6)	(357.2)	(369.4)
Education	2,054*	2,710**	3,238***	2,960***	2,785**
	(1,086)	(1,137)	(1,054)	(1,060)	(1,135)
House members	1,446	2,285	1,647	2,174	2,316
	(1,826)	(1,708)	(1,659)	(1,712)	(1,717)
Fishery	12,430	11,117	3,542	6,483	9,221
	(15,363)	(14,945)	(14,938)	(14,253)	(15,470)
Manufactory	-2,549	-4,147	-6,087	-6,585	-6,047
	(6,297)	(6,230)	(5,923)	(6,225)	(6,437)
Trade	1,147	-2,957	-6,081	-5,563	-4,678
	(5,758)	(5,619)	(5,245)	(5,384)	(5,593)
Other job	1,546	1,134	2,472	3,033	562.5
	(8,963)	(9,112)	(8,590)	(8,720)	(9,232)

(*Cont.*)

(*Cont.*)

Remittances	-17,836	-17,733	-13,177	-13,440	-16,232
	(21,043)	(23,081)	(19,239)	(22,469)	(21,533)
Subsidies	-15,971*	-12,345	-15,153*	-14,563*	-12,523
	(8,784)	(7,948)	(7,859)	(8,289)	(8,058)
Donations and grants	17,393	10,977	5,609	6,456	5,537
	(10,977)	(10,996)	(10,870)	(12,161)	(12,432)
Loans: bank	10,727	3,563	1,611	2,387	525.5
	(10,529)	(9,485)	(9,478)	(9,067)	(9,807)
Loans: MFI	2,244	4,650	2,584	2,557	3,968
	(15,006)	(15,715)	(14,606)	(14,715)	(15,689)
Loans: family/friend	-37.18	-5,132	-4,108	-5,430	-6,531
	(8,718)	(7,545)	(7,211)	(7,274)	(7,327)
Loans: other	8,385	-6,715	-4,698	-5,983	-7,146
	(17,144)	(14,859)	(13,564)	(13,899)	(14,785)
Real income	0.0410	0.138	0.164	0.150	0.143
	(0.147)	(0.153)	(0.153)	(0.148)	(0.156)
Observations	749	702	702	702	702
R-squared	0.237	0.294	0.316	0.309	0.299

Legend: The dependent variable is Loan Amount (the amount of the loan in December 2011 terms). Results come from OLS regressions with standard errors clustered at the borrower level. Regressions make use of time and village dummy variables (omitted for reasons of space but available upon request). Robust standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Determinants of credit defaults

Variables	(1)	(2)	(3)	(4)	(5)
Damaged			0.232		
			(0.437)		
Damage: family				1.262	
				(1.359)	
Damage: house				-0.819	
				(0.711)	
Damage: office building				-0.0170	
				(0.727)	
Damage: working tools				0.0754	
				(0.833)	
Damage: raw materials				0.0180	
				(0.616)	
Damage: econ. activity				0.725	
				(0.570)	
Sum of damages					0.0338
					(0.165)
Distance AMF		0.00308	0.00421	0.00750	0.00361
		(0.0207)	(0.0204)	(0.0211)	(0.0203)
Reason: new business		0.0427	0.0495	-0.131	0.0485
		(0.616)	(0.624)	(0.685)	(0.624)
Reason: improve		-0.127	-0.114	-0.318	-0.108
		(0.601)	(0.605)	(0.679)	(0.627)
Loan amount		1.83e-05***	1.79e-05***	1.80e-05***	1.81e-05***
		(4.02e-06)	(3.96e-06)	(4.01e-06)	(4.07e-06)
Interest rate		-0.0304**	-0.0306**	-0.0308**	-0.0303**
		(0.0146)	(0.0144)	(0.0151)	(0.0147)
Previous repaid loans		-0.129	-0.125	-0.161	-0.127
		(0.105)	(0.103)	(0.111)	(0.105)
Previous defaults		-0.556	-0.560	-0.562	-0.559
		(0.751)	(0.754)	(0.764)	(0.752)
Initiative: suggested		-0.930*	-0.934*	-0.984*	-0.920*
		(0.545)	(0.543)	(0.552)	(0.544)
Initiative: spontaneously		-0.478	-0.491	-0.388	-0.477
		(0.446)	(0.451)	(0.452)	(0.446)

(*Cont.*)

(*Cont.*)

Female	-0.134	-0.0175	-0.0318	0.0168	-0.0228
	(0.430)	(0.693)	(0.687)	(0.690)	(0.697)
Age	-0.0194	-0.0113	-0.0111	-0.0113	-0.0115
	(0.0155)	(0.0210)	(0.0208)	(0.0207)	(0.0211)
Education	-0.0436	-0.121	-0.115	-0.125	-0.119
	(0.0595)	(0.0774)	(0.0779)	(0.0834)	(0.0776)
House members	0.00206	0.0545	0.0481	0.0402	0.0522
	(0.120)	(0.158)	(0.157)	(0.154)	(0.156)
Fishery	1.942**	0.482	0.414	0.351	0.471
	(0.938)	(1.577)	(1.612)	(1.568)	(1.584)
Manufactory	-0.0367	-0.381	-0.400	-0.415	-0.391
	(0.364)	(0.408)	(0.412)	(0.423)	(0.410)
Trade	0.327	0.158	0.141	0.0874	0.151
	(0.368)	(0.433)	(0.437)	(0.468)	(0.431)
Other job	0.375	-0.736	-0.761	-0.810	-0.736
	(0.448)	(0.602)	(0.621)	(0.634)	(0.609)
Remittances	-2.741	-1.880*	-1.835*	-1.818	-1.876*
	(2.938)	(1.072)	(1.063)	(1.144)	(1.072)
Subsidies	0.561	0.637	0.630	0.717	0.630
	(0.527)	(0.711)	(0.712)	(0.787)	(0.716)
Donations and grants	0.479	0.558	0.480	0.662	0.511
	(0.579)	(0.731)	(0.740)	(0.747)	(0.762)
Loans: bank	-0.298	-1.205	-1.221	-1.368	-1.213
	(0.582)	(0.894)	(0.900)	(0.954)	(0.901)
Loans: MFI	1.146	0.512	0.525	0.551	0.517
	(0.957)	(0.710)	(0.700)	(0.707)	(0.704)
Loans: family/friend	-0.814**	-0.390	-0.388	-0.357	-0.396
	(0.405)	(0.501)	(0.506)	(0.526)	(0.510)
Loans: other	-0.478	0.474	0.510	0.406	0.501
	(0.932)	(0.793)	(0.795)	(0.782)	(0.784)
Real income	4.78e-06	3.27e-06	3.56e-06	3.53e-06	3.37e-06
	(6.29e-06)	(7.63e-06)	(7.65e-06)	(8.33e-06)	(7.72e-06)
Duration		-0.273***	-0.269***	-0.268***	-0.271***
		(0.0592)	(0.0602)	(0.0600)	(0.0602)
Frequency		-0.00591	-0.00692	-0.0139	-0.00620
		(0.0380)	(0.0380)	(0.0377)	(0.0381)
Observations	717	660	660	660	660
R-squared	0.530	0.642	0.642	0.646	0.642

Legend: The dependent variable is Default (dummy variable equal to 1 if the loan has not been repaid, 0 otherwise). Results come from Logit regressions with standard errors clustered at the borrower level. Regressions make use of time and village dummy variables (omitted for reasons of space but available upon request). Robust standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Determinants of credit defaults, only damaged

Variables	Coeff.	Robust Std. Err.
Female	0.205	-0.606
Age	-0.0074	-0.0212
Education	-0.0634	-0.0778
House members	0.243	-0.174
Fishery	3.257*	-1.808
Manufactory	-0.339	-0.466
Trade	-0.387	-0.49
Other job	-0.997	-0.685
Remittances	-	-
Subsidies	-0.678	-0.845
Donations and grants	0.79	-1.155
Loans: bank	0.88	-0.668
Loans: MFI	1.309	-1.444
Loans: family/friend	-0.563	-0.524
Loans: other	-	-
Real income	-7.55E-06	-8.89E-06
Distance AMF	0.0283	-0.0229
Reason: new business	-0.72	-1.661
Reason: improve	-0.872	-1.618
Loan amount	9.02e-06*	-4.65E-06
Interest rate	-0.0148	-0.0162
Previous repaid loans	-0.255	-0.156
Previous defaults	0.368	-0.522
Initiative: suggested	-0.506	-0.536
Initiative: spontaneously	-0.362	-0.487
Duration	-0.0328	-0.0811
Frequency	0.0563	-0.0379
DV years 2004-2006	3.882***	-0.622
DV years 2007-2011	-1.735	-1.687
Observations	335	
R-squared	0.474	

Legend: The dependent variable is Default (dummy variable equal to 1 if the loan has not been repaid, 0 otherwise). Results come from Logit regressions with standard errors clustered at the borrower level. The regression makes use of village dummy variables (omitted for reasons of space but available upon request). Robust standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A1: Determinants of loan interest rate

Variables	(1)	(2)	(3)	(4)	(5)
Female	2.030	-0.552	-0.886	-0.800	-0.675
	(4.083)	(2.221)	(2.192)	(2.242)	(2.240)
Age	-0.0879	-0.0470	-0.0439	-0.0593	-0.0432
	(0.133)	(0.0775)	(0.0768)	(0.0765)	(0.0763)
Education	0.461	0.283	0.352	0.300	0.294
	(0.472)	(0.245)	(0.249)	(0.256)	(0.247)
House members	0.160	0.463	0.419	0.521	0.471
	(0.878)	(0.449)	(0.455)	(0.458)	(0.455)
Fishery	-11.63**	-6.054	-6.691	-5.786	-6.198
	(4.985)	(5.019)	(4.999)	(4.979)	(4.992)
Manufactory	1.428	-0.102	-0.314	-0.132	-0.289
	(3.455)	(1.491)	(1.453)	(1.452)	(1.450)
Trade	-4.823	-0.439	-0.759	-0.694	-0.603
	(2.942)	(1.417)	(1.370)	(1.378)	(1.368)
Other job	-3.220	-2.255	-2.126	-2.153	-2.315
	(4.824)	(2.332)	(2.321)	(2.326)	(2.337)
Remittances	-7.587**	-3.535	-3.122	-2.039	-3.408
	(3.146)	(4.882)	(5.088)	(4.289)	(5.050)
Subsidies	-0.631	-2.848	-3.191	-4.151*	-2.879
	(4.422)	(2.316)	(2.291)	(2.263)	(2.327)
Donations and grants	-3.357	2.575	1.991	1.804	2.023
	(4.245)	(2.858)	(2.904)	(2.660)	(2.792)
Loans: bank	1.476	2.327	2.186	2.515	2.049
	(4.406)	(1.964)	(1.984)	(2.050)	(2.031)
Loans: MFI	-13.61**	-9.143	-9.279	-10.30*	-9.183
	(5.443)	(6.316)	(6.240)	(6.209)	(6.318)
Loans: family/friend	0.180	-0.0251	0.0216	-0.287	-0.177
	(4.057)	(2.198)	(2.172)	(2.138)	(2.209)
Loans: other	-5.808	2.503	2.576	2.388	2.431
	(6.913)	(6.929)	(6.944)	(7.004)	(6.925)
Real income	0.000186***	3.21e-05	3.41e-05	3.17e-05	3.22e-05
	(6.85e-05)	(2.85e-05)	(2.88e-05)	(2.87e-05)	(2.85e-05)

(Cont.)

(Cont.)

Distance AMF		0.248***	0.253***	0.246***	0.249***
		(0.0621)	(0.0623)	(0.0616)	(0.0624)
Reason: new business		-2.339	-2.334	-2.114	-2.145
		(2.679)	(2.694)	(2.801)	(2.752)
Reason: improve		-2.149	-2.142	-2.059	-1.904
		(2.130)	(2.146)	(2.357)	(2.284)
Loan amount		-4.44e-05***	-4.80e-05***	-4.72e-05***	-4.51e-05***
		(1.57e-05)	(1.58e-05)	(1.54e-05)	(1.57e-05)
Previous repaid loans		0.998***	0.958***	0.946***	0.992***
		(0.304)	(0.297)	(0.304)	(0.299)
Previous defaults		0.0792	0.112	-0.309	0.0938
		(2.061)	(2.031)	(1.986)	(2.050)
Initiative: suggested		-1.392	-1.418	-1.470	-1.453
		(1.440)	(1.430)	(1.437)	(1.470)
Initiative: spontaneously		2.611	2.433	2.174	2.505
		(1.706)	(1.718)	(1.773)	(1.759)
Duration		-1.871***	-1.866***	-1.877***	-1.870***
		(0.220)	(0.221)	(0.219)	(0.221)
Frequency		-0.187	-0.224	-0.183	-0.199
		(0.249)	(0.252)	(0.254)	(0.248)
Damaged				-1.366	
				(4.166)	
Damage: family				2.636	
				(2.916)	
Damage: house				4.371*	
				(2.344)	
Damage: office building				-4.752	
				(2.898)	
Damage: working tools				-0.378	
				(2.198)	
Damage: raw materials				1.743	
				(2.076)	
Damage: econ. activity			2.535		
			(1.953)		
Sum of damages					0.351
					(0.563)
Observations	749	690	690	690	690
R-squared	0.215	0.647	0.648	0.652	0.647

Legend: The dependent variable is the interest loan charged to the borrowers. Results come from OLS regressions with standard errors clustered at the borrower level. Regressions make use of time and village dummy variables (omitted for reasons of space but available upon request). Robust standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.