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Abstract

Conventional wisdom in economics holds that traditional credit and insurance networks are inapt for insuring against covariate risks such as natural hazards. We challenge this claim by examining changes in financial allocations in Rotating Savings and Credit Associations (Roscas), a popular group-based financial institution world-wide, in the aftermath of the 2004 Indian Ocean tsunami. With financial data from locations along the South Indian coast that were affected by this natural disaster to different extents, we estimate the causal effect of this devastating economic shock on financial flows between occupational groups, the price of credit and other loan characteristics. We find that the supply of funds in these local credit networks remained remarkably stable, while demand by self-employed members increased significantly. In response, substantial funds were channeled from wage-employed members and commercial investors to small and medium-scale entrepreneurs. We conclude that traditional non-market financial institutions may be more important for coping with covariate risks in low-income environments than commonly assumed.

JEL-Codes: O160, Q540, G230.

Keywords: risk-sharing, credit, informal insurance, Roscas, financial institutions, natural disasters.

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1 Introduction

Risk and uncertainty shape the lives of the poor around the developing world and natural disasters, most often in the form of drought or flood, are among the most severe shocks jeopardizing their livelihoods (World Bank (2014), p. 55). Since markets for insurance are largely missing, especially for the most vulnerable populations, households engage in various market and non-market transactions to deal with these risks, and credit plays an important role as an insurance substitute (Eswaran and Kotwal (1989); Besley (1995a) and Besley (1995b)). While idiosyncractic shocks appear to be well insured, often through informal credit transactions (Townsend (1994); Udry (1994); Fafchamps and Lund (2003); Fafchamps and Gubert (2007)), most authors in this literature express a general skepticism regarding the potential of local institutions and markets, including credit, for mitigating the effects of a covariate shock (Morduch (1999); Fafchamps et al. (1998); McKenzie (2003); De Mel et al. (2012)). However, given that natural hazards hit households and enterprises with considerable heterogeneity, even within villages or neighborhoods (Townsend (1994); Townsend (1995); Kurosaki (2017); Gallagher and Hartley (2017)), there appears to be scope for local risk sharing arrangements to deal with covariate shocks. This is of great importance given that formal insurance is largely absent and access to formal, inter-local finance as a risk-coping mechanism for natural disasters is often severely restricted (Becchetti and Castriota (2011); Berg and Schrader (2012); Gallagher and Hartley (2017)).

In this paper we provide causal evidence on the role of local credit for coping with a covariate shock. We empirically study the effect of one of the most devastating disasters in the last decades - the 2004 Indian Ocean tsunami - on local credit networks and analyze how credit flows between occupational groups, the price of credit and other loan characteristics change in response to the natural disaster. We first develop an analytical framework for measuring the extent of financial intermediation between sub-groups of network members. In our empirical analysis, we combine financial data covering 19,000 loans handed out in coastal and near-coastal locations of South India in 2004 and 2005 with geophysical data on the local severity of the tsunami to identify its causal effects within a difference-in-differences estimation framework. We focus on credit networks that had constituted before the tsunami to rule out selection effects. We find that the financial institution that we study is remarkably robust and stable in the aftermath of the shock - credit supply is inelastic and unaffected by the tsunami - which allows us to study nuanced demand responses to the natural disaster. According to our estimation results, sizeable funds are channeled to an especially affected group, self-employed individuals, for whom returns to lumpy replacement investments have previously been found to increase disproportionately in the aftermath of the Indian Ocean tsunami (De Mel et al. (2012)) as well as Hurricane Katrina (Deryugina et al. (2018)).

Our financial data is particularly suited for this endeavor. They come from Rotating Savings and Credit Associations (Roscas), which are group-based mutual financing schemes that combine inflexible contributions with flexible loans. In a Rosca, a group of individuals gets together regularly to contribute toward a common fund, also called a pot. At each meeting this fund is allotted to one group member. The allocation of pots to members is determined by concurrent competitive bidding for the loan interest rate. This way, Roscas provide structured, budget-balanced financial intermediation at the local level, i.e. among the group of Rosca participants, with regular, relatively small fixed savings and fairly large loans, one per Rosca member, which are flexible with regards to the timing of borrowing and the interest rate (Besley et al. (1993)). We approach the tsunami as a natural experiment to identify changes in allocations in this financial institution. For this exercise, the Roscas we consider have several attractive features. First, there is scope for gains from trade arising from the flexibility of the allocation mechanism of credit. The auction allotment mechanism implies that almost each of the over 19,000 loans in our data comes with unique terms, which reveal much about the nature of credit demand. Further, through the concurrent auctions, loan terms can react instantly to external events which affect credit demand. Second, Roscas are closed groups in which credit supply is inelastic once a group has formed. This allows us to separate effects on credit demand among usual market participants from effects on selection into participation, and to identify demand effects net of confounding supply side reactions. Third, the local financial networks are organized by a financial company in various locations in Tamil Nadu in a highly standardized form, which makes financial outcomes readily comparable across locations and over time, and allows the collection of large amounts of homogeneous financial data. Fourth, the wealth of our financial data allows us to address concerns regarding the validity of our empirical research design by establishing the similarity of affected and unaffected locations before the tsunami and by conducting placebo tests to corroborate the common trend assumption in our difference-in-differences estimations. Fifth, Roscas form an important part of informal credit markets around the globe (Besley (1995b)) and they are particularly common in South India, where they are called chit funds.[1] This generates scope for important policy implications regarding the potential of local financial networks for dealing with covariate shocks.

Our empirical analysis yields three main results. First, we find no changes in the supply of funds in response to the tsunami, indicating that the Roscas we study form a stable financial system that is robust to the large shock of the tsunami. Second, we find a significant increase in the competition for loans on the demand side in response to the tsunami, which is manifested by an increase in the price of credit by around nine percent in coastal locations. Third, we find a large increase in credit flows to Rosca participants who are entrepreneurs. Their debt increases from close to zero to more than eighty percent of their total borrowing capacity in these Roscas. This translates into an additional debt of 526 US Dollars (not purchasing-power adjusted) per self-employed Rosca member and 1.4 million US Dollars for all self-employed members in the five coastal locations in our sample.[2] These funds originate to similar extents from wage-employed Rosca members and a commercial investor, who arbitrages across groups and locations.

Our research contributes to several strands of literature. First, in the literature on credit as insurance substitute we see an unresolved antagonism regarding the potential of local financial intermediation for coping with covariate shocks. Research on the topic of credit and risk in low-income countries has largely focused on idiosyncratic shocks, and indeed numerous related studies on income

[1]Eeckhout and Munshi (2010) state that deposits in registered Roscas formed 12.5 percent of bank credit in Tamil Nadu and 25 percent of bank credit in Kerala in the 1990s. According to Kapoor et al. (2011), this figure stood at 55 percent for Tamil Nadu in 2006 with an increase of five percent per year between 2003 and 2006. There are no reliable figures on the prevalence of unregistered Roscas, but Kapoor et al. (2011) conjecture that the amount transacted in these informal groups is even larger than in the registered ones.

[2]For comparison, India's GDP per capita stood at 707 US Dollars in 2005.

fluctuations and consumption smoothing show that households are remarkably well insured against these risks via credit and bilateral transfers (Townsend (1994); Ligon et al. (2002); Fafchamps and Lund (2003); Chiappori et al. (2014)), or state-contingent loan repayment (Udry (1990), and Udry (1994); Fafchamps and Gubert (2007)). Perhaps most closely related to our study is Fafchamps and Lund (2003), who study how informal financial transactions respond to idiosyncratic shocks in risk-sharing networks in the Philippines. They find that informal loans to a household from its risk-sharing network increase when the household experiences an economic shock. On the other hand, research on credit as insurance mechanism in the face of covariate shocks is scarce, despite the fact that natural hazards severely jeopardize the livelihoods of the poor.[3] The small body of research on the role of credit for coping with such shocks is mostly concerned with formal credit and the effect of access to banks and microfinance institutions on consumption smoothing and the capacity to recover from economic losses caused by disasters (Del Ninno et al. (2003); Gitter and Barham (2007); Khandker (2007); Sawada and Shimizutani (2008)). These observational studies face considerable challenges regarding the empirical identification of the causal effect of access to finance.[4] A notable exception is De Mel et al. (2012), who study enterprise recovery following the Indian Ocean tsunami in Sri Lanka. They randomly assign and deliver cash grants to microenterprises and they find that firms with access to funds recover much faster, which they attribute to the high returns to replacement investments in this situation.

Our contributions to this literature are that, first, our focus is on an entire market rather than single households or enterprises. We study the effects of a covariate shock on financial allocations in a popular indigenous financial institution that closely resembles informal credit markets (Munshi (2005)) and reaches out to many more households in our study context than banks (Kapoor et al. (2011)). Second, our analysis employs rich and detailed financial data, which allows us to elicit changes in the allocation of funds between occupational groups and in the price of funds. And third, we show that financial intermediation in these semi-formal networks responds quickly and channels funds to a group that is especially severely affected by the tsunami, small to medium-scale entrepreneurs. This central finding is consistent with and complements the results obtained by De Mel et al. (2012). Importantly, we document financial flows to entrepreneurs in actual credit networks, whereas the funds in De Mel et al. (2012) are helicopter drops of money provided by the researchers.

Second, we contribute to the literature on Roscas as an important financial institution in developing and transition economies. Firstly, there are a number of studies, theoretical and empirical, showing how Roscas generate welfare gains from mutual insurance when participants are subject to idiosyncratic shocks (Kuo (1993); Calomiris and Rajaraman (1998); Klonner (2010) and Klonner (2008)). These papers stress the importance of the concurrent auction credit allocation mechanism of bidding Roscas. The focus in this literature is exclusively on idiosyncratic income or expenditure

[3] To name only a few papers, Rose (1999) documents female excess mortality in response to droughts in India. Maccini and Yang (2009) find lasting effects of early-life rainfall on female adult outcomes in Indonesia. Duflo and Pande (2007) document substantial effects of drought on poverty in rural India. Burgess et al. (2017) find that hot days and drought substantially increase contemporaneous mortality in rural India. Kurosaki (2015) finds a negative effect of floods on household consumption in rural Pakistan. Kahn (2005) finds that earthquakes, extreme heat, flood, landslide and windstorms result in higher death tolls in low-income countries than in high-income countries.

[4] Better empirical identification has been achieved in recent work that considers migration as a coping strategy for dealing with environmental hazards (Yang and Martínez (2007); Gröger and Zylberberg (2016)).

shocks. Our contribution is that we show empirically how bidding Roscas also provide insurance in the aftermath of a covariate shock by intermediating between different occupational groups. Secondly, we contribute to a theoretical literature on Roscas that addresses their optimality as a savings institution (Besley et al. (1993); Besley et al. (1994)), the choice of allotment mechanism, auctions versus lotteries (Kovsted and Lyk-Jensen (1999); Anderson et al. (2009)), and the role of Roscas as a commitment device to reach a savings objective (Basu (2011)). Our contribution here is that, with an axiomatic approach, we derive a basic analytical framework for financial allocations in Roscas, which relates the Rosca-specific concept of the timing of borrowing to the more common concept of debt.

Third, we contribute to the literature on natural disasters and financial markets. The common finding in this literature is that, while access to formal finance helps mitigating the consequences of a covariate shock, the supply of funds tends to be severely restricted in the wake of a natural disaster.[5] Our contribution to this literature is that, unlike most studies, we are able to separate demand from supply side effects on the price of funds since supply is inelastic in the short run in our institutional setting. Further, in this semi-formal, local financial institution, we do not observe any market contractions in the aftermath of the tsunami, while we confirm previous findings of an intensified demand for funds.

Fourth, we contribute to a literature on non-market institutions in economic development. Traditionally, there has been a dichotomy between traditional non-market institutions and modern market institutions (Geertz (1962); Besley and Coate (1995); Munshi (2005); Eeckhout and Munshi (2010)). Geertz (1962) has identified a lack of focus on intermediate, so-called middle-rung, institutions bridging the gap between these two. Roscas operated by financial companies are an important example of such middle-rung institutions: first, they combine traditional enforcement technologies based on social-capital and hassling with modern ones based on the legal system (Munshi (2005)), and second, they combine traditional local financial intermediation, which implies market fragmentation, with elements of spatial market integration, through the participation of a single commercial investor in all locations. We contribute to this literature by demonstrating how financial allocations reflect this synthesis of traditional non-market and modern market elements: funds to entrepreneurs are supplied to similar extents by local participants with other occupations and the commercial Rosca investor.

The paper is organized as follows. Section 2 takes a closer look at the functioning of Roscas and the financial and geophysical data used in the empirical analysis. In section 3 we present our empirical approach. First, we introduce the general difference-in-differences estimation strategy. Second, we develop an analytical framework for measuring financial intermediation between sub-groups of Rosca participants. Third, building on these two pillars, we derive our estimating equations. Section 4 presents the results. Robustness checks and a number of extensions are presented in section 5. Section 6 concludes.

[5] Berg and Schrader (2012) study microfinance loans after volcanic eruptions in Ecuador; Cortés and Strahan (2017) study multi-market banks after various natural disasters in the USA; and Gallagher and Hartley (2017) study household finance in the form of home loans, auto loans, credit card accounts, and student loans after Hurricane Katrina in New Orleans, USA.

2 Background and data

2.1 Geophysical data - the December 2004 Indian Ocean tsunami

On December 26 in 2004, an earthquake in Sumatra, Indonesia, caused tsunami waves to hit the coast of India. The giant tsunami waves of three to eleven meters in height penetrated up to three kilometers inland, causing damage in the states of Andhra Pradesh, Kerala, Tamil Nadu and the Union Territory of Pondicherry on the Indian mainland. The coast of Tamil Nadu was hit especially hard with 7,995 people killed, accounting for over 60 percent of all casualties due to the tsunami in India. 230 villages and 418 hamlets were flattened completely and more than 470,000 people had to evacuate their homes. In addition, the tsunami caused massive destruction of infrastructure, agricultural soil, and productive assets in enterprises, including shops and small manufacturing businesses (Asian Development Bank (2005); Athukorala and Resosudarmo (2005); Tamil Nadu Government (2005b)). Fishery and related activities are important for livelihoods along the coast of Tamil Nadu and fishermen living close to the coast were most severely affected by the tsunami's destruction, accounting for 38 percent of the tsunami's damage, followed by small business owners (18 percent) and farmers (5 percent) (Shoji et al. (2011)).[6]

The tsunami hit small business owners especially hard as documented by De Mel et al. (2012) for microenterprises in Sri Lanka. Not only did they lose household assets, but they also suffered from losses of business assets as well as disruptions in supply and marketing chains due to destroyed infrastructure.[7] While grants from formal and transfers from informal sources covered losses in household assets, lost business assets had to be replaced mainly through loans. Their study on enterprise recovery documents that access to capital is of utmost importance for microenterprises' recovery in the aftermath of this natural disaster given the extraordinarily high returns to the necessary replacement investments. In particular, retailers benefitted disproportionately from replenishing inventories.

For our empirical analysis, we use geophysical data from a survey conducted by the Department of Earthquake Engineering at the Indian Institute of Technology, Roorkee (Maheshwari et al. (2005); Narayan et al. (2005)). The data set contains the coordinates of 40 survey points along the Tamil Nadu coast together with the tsunami waves' maximum run-up height in meters and the observed damage intensity on a 12-step ordinal scale by Papadopoulos and Imamura (2001), which ranges from *not felt* (1) to *completely devastating* (12).[8]

[Figure 1 about here]

To merge the financial and geophysical data, we calculate the spatial coordinates of the Rosca branches in our financial data from the branch addresses. We focus on branches within a distance

[6] Official sources state that 16,772 fishing boats were fully and 19,305 partly damaged. Farmers suffered from losses of agricultural produce in storage and 16,083 cattle as well as soil degradation and salinization of 8,460 hectares of agricultural land and 669 hectares of horticultural land (Asian Development Bank (2005); Tamil Nadu Government (2005b)).

[7] The double affectedness as local residents and business owners has also been documented for small business owners affected by Hurricane Katrina that hit the southeast coast of the USA in August 2005 (Runyan (2006)).

[8] Other common definitions of tsunami intensity are Soloviev's (1970) $i=\log_2(\sqrt{2}*\text{ run-up height})$, which is also used by the United States' National Geophysical Data Center, and Shto's (1993) $i=\log_2(\text{run-up height})$. Since both of these measures are just monotonic transformations of the wave run-up height, we choose to focus on just the run-up height alongside the damage intensity.

of 25 kilometers of the coastline to ensure that all sample branches are embedded in a homogeneous economic environment prior to the tsunami. We assign to each of these 14 branches the waves' run-up height and the observed damage intensity at the nearest survey location by Maheshwari et al. (2005) and Narayan et al. (2005). Given an inundation distance of no more than three kilometers along the coastline of Tamil Nadu (Narayan et al. (2005)), we assign a run-up height and damage intensity of zero to the nine branches located at least five kilometers away from the coastline. In the sequel, we will refer to the latter as 'near-coastal' and the other branches as 'coastal'.

[Table 1 about here]

At the five coastal branch locations in our sample, the run-up height ranges from three to eleven meters and averages at 5.8 meters (Table 1). The damage intensity ranges from 6.5 (*damaging)* in Tuticorin, which was shielded by Sri Lanka's land mass, to ten (*very destructive*) in Nagappattinam, which was the most affected city on the Indian coast with 6,065 casualties (around 76 percent of all deaths in Tamil Nadu, Tamil Nadu Government (2005b)). The average damage intensity in the five coastal branches is close to eight (*heavy damaging*).

2.2 Financial data - Roscas

Our financial data comes from semi-formal bidding Roscas. In a Rosca, a group of individuals gets together regularly to save and borrow (Besley et al. (1993)). At each meeting, every member of the group contributes a fixed amount to a common pot, which is allocated to one of the participants in turn. Every participant receives the pot once during the course of a Rosca. In our Roscas, the pot is allocated by an oral ascending bid auction, where the highest bidder receives the pot less the winning bid. Once a participant has received a pot she is ineligible to bid in any of the subsequent auctions. The winning bid amount is shared equally by all participants of the Rosca as a so-called dividend. This creates an interest component for borrowings and savings.

Example *To illustrate these rules, consider the following three-person Rosca, which meets once a month. Each participant contributes $10, which implies a pot of $30. Suppose the winning bid in the first month is $12. Each participant receives a dividend of $4. In the second month, when there are two eligible bidders left, suppose the winning bid is $6. Each participant receives a dividend of $2. And in the final month, there is only one participant eligible for the pot, so that there is no auction and no dividend.*

Month	1	2	3
Winning Bid	$12	$6	$0
Dividend	$4	$2	$0
Payoffs			
First Recipient	$12	-$8	-$10
Second Recipient	-$6	$16	-$10
Last Recipient	-$6	-$8	$20

The first recipient is a borrower and her loan carries a positive interest rate: she receives $12 in the first period (the pot of 30 minus her contribution of 10 minus the winning bid of 12 plus *the dividend of 4) and repays \$8 and \$10 in months 2 and 3, respectively. The last recipient is a saver, who is rewarded with a positive savings interest rate: she saves \$6 for two months and \$8 for one month and receives \$20 in the last month. The second recipient is a saver for one month and, subsequently, a borrower for one month.*

As shown in the example, the recipient of the first pot is a pure borrower and the recipient of the last pot is a pure saver. For all auctions in between, the participants are savers for some time and borrowers afterwards. Important parameters of a particular Rosca are the number of participants, which is equal to the Rosca's duration in months, and the monthly contribution of each member. We will call a particular combination of Rosca duration and monthly contribution a Rosca denomination.[9] Each denomination has its own pot value and, according to the organizer, caters to different financial needs of customers. An important feature of bidding Roscas for our analysis is that, once a group has started, the supply of funds is completely inelastic.

The data we use come from one single commercial Rosca organizer operating 78 branches in the state of Tamil Nadu in 2004 and 2005. Rosca groups are formed by enrollment of interested individuals into lists, which are posted in each branch. Hence the members of a given group may or may not know one another from outside the Rosca. There are no incentives for peer selection, monitoring or enforcement since the Rosca organizer fully insures its customers against default of other members of the same group. The company applies the following measures to enforce repayment. First, upon receiving the pot, members may be screened. Screening of a member occurs only after winning an auction and involves the recording of the borrower's occupation, income, and employer or type of business. Second, the organizer may request guarantors, or cosigners, who pledge to step in for any missed future contribution owed by the borrower. If the winner of an auction does not pass the screening procedure or is unable to furnish the requested number of guarantors, the organizer may refuse to lend and re-auction the pot.[10] Third, borrowers who are in arrear are pressured not only through letters and phone calls but also through visits to their homes. Fourth, ultimately the company takes legal measures against borrowers and cosigners in case of default. These measures range from a letter signed by a lawyer to obtaining a formal court order. Fifth, there is an individual dynamic incentive. The company keeps black lists of defaulters, who are denied participation in future Roscas. The organizer does usually not require traditional physical collateral. In return, the organizer gets compensated by a small sign-up fee of each member, a commission of five percent of each allocated pot, and the first pot in each Rosca, which he receives without any deduction.[11]

Our sample consists of 19,594 loans made between January 2004 and October 2005, around one year before and after the tsunami, in 1,069 different groups. We use only groups that started before December 26, 2004, to rule out effects of the tsunami on selection of individuals into Roscas, and after January 1, 2002, when there was a change in the regulatory legislation, to ensure all Rosca

[9] Appendix Table C.1 gives an overview of all denominations in our sample.

[10] While such instances are not recorded in our data, the organizer told us that they are very rare because the requirements for obtaining a loan are clearly communicated in the agreement signed by each customer up-front.

[11] The Roscas that we consider are - in our view - not informal as the organizing company is an officially registered non-bank financial company, which notifies Tamil Nadu's Chit Fund Registrar of each Rosca group. However, chit fund companies face far less supervision and regulatory intervention than banks, the usual providers of formal finance (Kapoor et al. (2011)). Our classification differs from Eeckhout and Munshi (2010), who refer to them as informal. We prefer "semi-formal" to highlight the contrast to Roscas in India that are unregistered.

groups in the sample are homogenous with respect to regulatory conditions.[12] Further, as elaborated above, we restrict the sample to coastal and near-coastal branches located not farther away than 25 kilometers from the coastline.[13] We will consider departures from this choice in the robustness checks section.

[Table 2 about here]

The pot value in our sample ranges from Rs. 10,000 to Rs. 1,000,000 with an average of around Rs. 57,000 (Table 2).[14] The average winning bid in the sample is Rs. 13,131 with a minimum of Rs. 500 and a maximum of Rs. 300,000. In order to compare winning bids across Roscas from different denominations, we define the relative winning bid as the winning bid divided by the pot value. This figure ranges from five to 40 percent with a sample mean of 17.4 percent.[15]

Regarding screening and loan terms, recording of a borrower's income occurs in 78.4 percent and employment or type of business in 65.6 percent of all loans. At least one cosigner is attached to 54 percent of all loans and the average number of cosigners is 1.1.[16] At the time of data collection, in November 2005, 44.4 percent of all loans were in arrear and the arrear amount equaled 3.3 percent of a pot on average. Legal measures were taken for 8.6 percent of all loans. Columns 4 to 6 of Table 2 contain a comparison of Rosca and loan characteristics before the tsunami in coastal and near-coastal branches. The p-values in column 6 support the hypothesis that the distribution of these characteristics across coastal and near-coastal branches is as good as random.

Different types of participants use Roscas as a savings or borrowing device to different extents. Interviews with Rosca participants revealed that Rosca participation is driven by a variety of motives, such as the accumulation of funds for productive investments and lumpy consumption items. Others value Roscas primarily as a financial investment, since returns to savings are larger than in banks (see also Kapoor et al. (2011)). The organizer pointed out to us that he deliberately mixes different occupational groups to maximize gains from trade within each Rosca group. According to the figures in Table 2, in our sample 11.3 percent of pots for which the recipients's occupation is recorded go to self-employed, 29.2 percent to wage-employed, and 7.8 percent to members who are not employed (this group comprises housewives, students and pensioners).[17] Finally, 51.6 percent (33.9 percent of all pots in our sample) go to a single corporate financial investor ('institutional investor' for short), who entertains close business relations with the organizer. His purpose is to bid when other demand

[12] The Tamil Nadu government imposes a bid ceiling on winning bids of the pot value. Effective from January 1, 2002, the ceiling on winning bids was lifted from 30 to 40 percent in an amendment to the Tamil Nadu Chit Fund Act.

[13] We did not collect data from branches in the state capital Chennai, which was also affected by the tsunami. As a metropolis with 4.5 million inhabitants in 2005, it differs greatly from all other branch locations that are included in our main statistical analyses.

[14] The exchange rate, not purchasing-power parity adjusted, on December 25, 2004 is 43.62 Rs./US Dollar and will be used for all currency conversions. The average pot hence equals around 1,300 US Dollar.

[15] The minimum of the relative winning bid at five percent is due to the organizer's commission charged at every auction. On the other end, the Tamil Nadu Chit Fund Act mandates a bid ceiling of 40 percent of the pot value. Once bidding reaches the ceiling of 40 percent of the pot, the pot is allocated by lottery. Winning bids equal to the bid ceiling occur in 8.4 percent of all auctions and 69.3 percent of auctions in the second round of a Rosca - the first pot is always allocated to the organizer as part of his remuneration.

[16] Data on income, cosigners and arrears is only considered for the 12,960 auctions not won by the institutional investor (see below for details regarding the peculiarity of this participant group).

[17] Table 2 reports occupations of auction winners in the full sample, including auctions for which no occupational information is recorded by the organizer.

is low. This ensures an attractive rate of return for other, non-corporate, members who value chit funds primarily as a financial investment. At the same time the institutional investor has a gain from making arbitrage profits across groups and branches. By doing so, he reduces fragmentation in the chit fund segment of the financial market by implicitly providing some financial intermediation across groups and locations. This feature is absent in traditional informal Roscas, where all members, including the organizer, are local.

[Figure 2 about here]

Important for our later econometric analysis, the occupational composition of winners of pots varies systematically over the course of a Rosca. Figure 2 illustrates this in two alternative ways for Rosca auctions in 2004, prior to the tsunami. Panel (a) depicts the occupational composition of auction winners and panel (b) the relative frequency of winning an auction for each occupational group. To aggregate the data from Rosca denominations with different durations, Rosca rounds are categorized into duration deciles. Accordingly, self-employment and wage-employment are recorded more often among recipients of early pots, while the institutional investor obtains pots primarily around the middle of a Rosca's duration.[18] During the first seven deciles of these Roscas, the organizer did not record the occupation for around 20 percent of auction winners and this figure increases sharply in later rounds (with 90.4 percent in the last decile), where the organizer's lending risk becomes minimal.[19] We will address this issue in detail later on.

3 Empirical approach

We combine financial data on Roscas with geophysical data on the local severity of the tsunami to empirically assess the effect of the December 2004 tsunami on the flow of funds, the price of credit and other loan characteristics. This section outlines the empirical strategy of our analysis. First, we introduce the basic difference-in-differences estimation strategy, in which we approach the tsunami as a natural experiment. Second, we develop a novel analytical framework, which delivers measures of debt and claims (or savings) in a Rosca that will be used to quantify the extent of financial intermediation between different occupational groups of Rosca participants. Building on this framework, we finally derive the estimating equations.

3.1 The tsunami as a natural experiment

Throughout, we will conduct difference-in-differences (DID) estimations, in which we compare auction outcomes in different locations, before and after the tsunami. In a first step, we divide all auctions in the sample into auctions taking place before the tsunami and auctions taking place after the tsunami on December 26, 2004. In a second step, we assign the respective local severity of the tsunami to all auctions in the latter set.

[18] For practical purposes, we lump together the first pot of each Rosca, which goes to the organizer, with the pots going to the institutional investor through the memberships he holds in a Rosca. It is only due to this classification that the institutionl investor obtains 42.5 percent of pots in the first decile in Figure 2.

[19] In fact, the organizer told to us that he often strikes a deal with winners of late pots where he deducts the remaining contributions from the amount paid out to the winner, thus eliminating any exposure.

We structure the observations in our Rosca dataset according to branch (indexed by b), Rosca denomination (indexed by d), group (indexed by g) and round (indexed by t).[20] Our basic estimating equation is

$$y_{bdgt} = \rho_{bd} + \sum_{m=1}^{22} \gamma_m Month_{bdgt}^m + \beta \; tsunami_b \times after_{bdgt} + u_{bdgt}, \tag{1}$$

where the dependent variable y_{bdgt} is a financial outcome in round t in Rosca group g of denomination d in branch b. The term ρ_{bd} is a fixed effect to account for unobserved branch and denomination-specific heterogeneity. We define $Month_{bdgt}^m$ as a dummy equal to one if auction $bdgt$ occurs in month m ($m = 1, ..., 22$, where 1 corresponds to January 2004). Effectively, $\gamma_m Month_{bdgt}^m$ is a month fixed effect for month m. The variable $tsunami_b$ is a measure of local tsunami intensity, either the *run-up height* of the tsunami waves or the *damage intensity* in location b. The dummy variable $after_{bdgt}$ indicates whether an auction took place after the tsunami. Hence it equals zero for $m = 1, ..., 12$ and one for $m = 13, ..., 22$. So the difference-in-differences strategy is implemented through the cross-sectional fixed effects, the month fixed effects, and the interaction term of interest $tsunami_b \times after_{bdgt}$.

To account for intra-branch as well as serial correlation, standard errors are clustered at the branch level, which is the cross-sectional unit at which the explanatory variable of interest varies (see Bertrand et al. (2004)). A potential challenge is that this clustering rule leaves us with a relatively small number of clusters, 14 in our specification, for which the conventional cluster-robust standard errors may be downward biased (Cameron et al. (2008)). Therefore, as recommended by Cameron and Miller (2015), we also report bootstrap-based statistical inference following the methods developed by Cameron et al. (2008) in our main regressions.

3.2 Financial intermediation in Rotating Savings and Credit Associations

The objective of this section is to provide an accounting framework for financial flows, debt and claims between different occupational groups of Rosca members. It is clear from the example given above that recipients of early pots are effectively borrowers and recipients of late pots savers. We will first show how the rank order of receipt of a pot can be used to calculate a measure of debt (or savings) for each member of a Rosca. Secondly, we extend this accounting framework to debt held by different groups of Rosca members.

3.2.1 Rank and debt in bidding Roscas

In a Rosca that lasts for T months there are T individuals, who each contribute Rs. z per month. To allocate the collected contributions of zT, the *Pot*, there is an auction in each month t except the last. After each auction, the winning bid p_t, the *price* of pot t, is equally shared by all participants. The net payoff to the winner of the pot in period t is $-z + zT - p_t + \frac{p_t}{T} = \left(1 - \frac{1}{T}\right)(Pot - p_t)$ and

[20] To give an example: suppose there are five Roscas of the denomination with 40 rounds and monthly contribution of Rs. 500, which we shall denote by $d^{\#}$, in the Pondicherry branch, which we shall denote by b'. Then g will run from one through five for the pair $b'd^{\#}$. Moreover, for each group belonging to denomination $d^{\#}$, t runs from one through 40. Notice that t does not denote the calendar month in which said round occurred but only refers to the round within a given Rosca.

$-z+\frac{p_t}{T}=-\frac{1}{T}(Pot-p_t)$ for all other participants. We will call $Pot-p_t$ the 'effective pot' and denote it by $\widetilde{Pot}_t$. As can be seen from the payoffs, the winner of an auction has a net payoff of $\frac{T-1}{T}\widetilde{Pot}_t$, while all other $T-1$ participants pay $\frac{1}{T}\widetilde{Pot}_t$.

We approach the issue of financial intermediation in a Rosca by clarifying first who owes how much to whom at any given month in the Rosca. As far as the direction of changes in debt and savings over Rosca rounds is concerned, it is clear that a participant who does not win the pot in round t increases her savings (or decrease her debt), while the winner of that pot increases his borrowings (or decreases his savings). The challenge, on the other hand, is to aggregate the net payoffs of preceding rounds into a single measure of individual debt in a given month of a Rosca. We will proceed in two steps. First, we spell out four (as we think) sensible requirements for measuring debt in Roscas and show how these axioms characterize a single measure of debt for each member at each point in time of a Rosca. Second, guided by considerations of analytical convenience rather than axioms, we will construct a measure of average debt for each Rosca participant, which aggregates her debt in each period into a single summary statistic.

Without loss of generality, we index a participant i by the round in which she wins the pot, which is also commonly called her 'rank' (e.g. Anderson et al. (2009)). Our four requirements for debt of participant i in round t are:

Axiom 1 *Additivity: Debt of participant i at time t is the sum of the present values at time t of her net payoffs accruing in periods 1 through t.*

Axiom 2 *Exponential discounting: The present value at time t' of a payoff occurring to participant i in t, y_{it}, is $y_{it}(1+r_{it})^{t'-t}$.*

Axiom 3 *Variation in the implicit interest rate: The implicit interest rate for payoffs in period t may depend on t but is the same for all Rosca members, $r_{it}=r_t$.*

Axiom 4 *Evening-up: In the last round, the debt is zero for all Rosca members.*

To provide some intuition for these conditions, we essentially conceptualize a Rosca as a market, where - at any point in time - there is an identical interest rate for borrowings and savings. The interest rate is fixed in the sense that, for savings and borrowings occurring in t, it is locked-in until the termination of the scheme. On the other hand, the interest rate may fluctuate over time.

Proposition 1 *Axioms 1 through 4 imply that*

$$\begin{aligned} D_{it,t'} &= \sum_{\tau=1}^{t}(1+r_\tau)^{t'-\tau}\left(x_{i\tau}-\frac{1}{T}\right)\widetilde{Pot}_\tau, \\ \textit{where } r_t &= \left(\frac{Pot}{\widetilde{Pot}_t}\right)^{\frac{1}{T-t}}-1,\ t=1,...,T-1, \end{aligned} \tag{2}$$

where $x_{i\tau}$ is an indicator equal to one when i equals τ and zero otherwise, and $D_{it,t'}$ denotes the present value at time t' of participant i's debt accumulated over the periods 1 through t.

The proof of this characterization result is relegated to Appendix A. We shall make three remarks on this proposition here. First, the discount rate for period t payoffs, r_t, equals roughly $\widehat{p}_t/(T-t)$, where $\widehat{p}_t$ is the winning bid in period t relative to the full pot, zT. Hence winning bids reflect the implicit interest rate in a simple fashion: p_t is just the compound interest for a loan with a gross repayment equal to Pot and due $T-t$ periods later. Moreover, the terminal value, that is the future value at time T, of the net payoffs occurring in period t is simply $\left(1-\frac{1}{T}\right) Pot$ for the winner of the t'th pot, and $-\frac{1}{T}Pot$ for all other participants. As a consequence, the terminal value of i's debt in round t, $D_{it,T}$, equals $-\frac{t}{T}Pot$ if she has not won an auction in the first t rounds and $\left(1-\frac{t}{T}\right) Pot$ otherwise. Second, while the definition of r_t by the equation $\widetilde{Pot}_t(1+r_t)^{T-t} = Pot$ as the round t implicit interest is straightforward and intuitive, the proposition implies uniqueness in the sense that this sequence of implicit interest rates is the only one satisfying the requirements of additivity, exponential discounting and evening-up. Finally, with our axioms, which allow for a different implicit interest rate for the payoffs in each round, debt is always well-defined. This would in general fail to be the case for winners of intermediate pots if axiom 3 was replaced by the requirement that the implicit interest rate is time-invariant for each participant.

To quantify the extent of financial intermediation in a Rosca, we are interested in a measure of *average debt* over the course of a Rosca for a given participant, where the average is taken over the T months the Rosca lasts. For any participant i, we choose to calculate the average of the terminal values of debt over the Rosca cycle as

$$\frac{1}{T}\sum_{t=1}^{T} D_{it,T}.$$

This measure has the unique advantage of not depending on any of the winning bids because the terminal values of all net payoffs occurring over the course of the Rosca equal either $\left(1-\frac{t}{T}\right) Pot$ or $-\frac{t}{T}Pot$, as discussed above, which greatly eases the empirical analysis.

Proposition 2 *Participant i's average debt over the Rosca cycle, evaluated at the termination of the Rosca, is*

$$D_i = \frac{1}{T}\sum_{t=1}^{T} D_{it,T} = \frac{Pot}{2}\frac{T+1-2i}{T}, \tag{3}$$

which can equivalently be written as

$$D_i = \frac{1}{T}\sum_{t=1}^{T} Pot\ T\ x_{it}\left(\frac{1}{2}\frac{T+1}{T} - \frac{t}{T}\right). \tag{4}$$

The proof of proposition 2 is relegated to Appendix A. The first part of this proposition says that the average debt of a Rosca participant solely depends on her rank in the Rosca, indeed in a linear fashion. The numerator of the second fraction on the right hand side of equation 3 is just the duration of borrowing, which is the difference between the total duration of the Rosca and a participant's rank. To provide three instructive examples, the winner of the first pot, who holds the first rank ($i = 1$), is a borrower for $T-1$ months. Her debt, evaluated at its terminal value, equals $\frac{T-1}{T}Pot$ after the first round of the Rosca. On average, however, her debt equals only one half of that figure, $\frac{T-1}{2T}Pot$, because repayment is effected in equal installments, whose terminal value is Pot/T, over $T-1$ periods. Hence the terminal value of her debt decays linearly from $\frac{T-1}{T}Pot$ to zero over the course of the Rosca. Conversely, the winner of the last pot ($i = T$) is always a saver, for $T-1$ months, and her average savings are equal to her savings in the middle of the Rosca, so her debt is $-\frac{T-1}{2T}Pot$ when evaluated at its terminal value. A participant who holds precisely the middle rank ($i = (T+1)/2$) has equal time spells of saving and borrowing, and hence has an average debt of zero.

Example continued *Consider the same example of a Rosca with three members and a monthly contribution of \$10 per member given further above.*

Month	1	2	3
Winning Bid	\$12	\$6	\$0
Payoffs			
First Recipient	\$12	-\$8	-\$10
Second Recipient	-\$6	\$16	-\$10
Last Recipient	-\$6	-\$8	\$20
$D_{it,T}$ (debt balance evaluated in period $T = 3$)			
First Recipient ($i = 1$)	\$20	\$10	\$0
Second Recipient ($i = 2$)	-\$10	\$10	\$0
Third Recipient ($i = 3$)	-\$10	-\$20	\$0

The three members' average debt over the course of the Rosca, D_i, hence equals \$10 for the first, \$0 for the second and -\$10 for the third recipient.

Equation 4 illustrates how D_i can be estimated as a sample mean from a data set with one Rosca in which each Rosca round contributes one observation. For this exercise, the variables needed are the two time-varying ones, t and x_{it}, and the two time-invariant ones Pot amount and Rosca duration, T. This formulation will guide the construction of dependent variables in the empirical analysis.

3.2.2 Financial flows between occupational groups

We now extend the preceding framework to derive a measure of financial intermediation between groups of Rosca participants. Suppose there are two groups of participants, entrepreneurs, A, and others, O. Members of A make for $s_A T$ participants of the Rosca, and members of O for the remaining $(1-s_A)T$ participants, where s_A refers to the share of members with occupation A in group g. Drawing on our previous derivations, the net payoff to group A in month t is $y_t^A = (x_t^A - s_A)\widetilde{Pot}_t$, where x_t^A is a dummy variable equal to one if the winner of pot t belongs to A. We denote by $\bar{t}^A$ the mean round in which members of A win pots, which may also be called the average rank of group A. The following corollary gives formulas for the average debt of a group of participants in a Rosca. Notice that 'average' here refers to mean debt with respect to Rosca rounds, not individuals. Hence average debt of group A is cumulated over all members of A and equal to the sum $\Sigma_{i\in A} D_i$.

Corollary 1 *The average debt of a group of Rosca participants, A, which comprises $s_A T$ members, evaluated at the termination of the Rosca, is*

$$D^A = s_A \frac{Pot}{2}(T + 1 - 2\bar{t}^A), \tag{5}$$

which can equivalently be written as

$$D^A = \frac{1}{T}\sum_{t=1}^{T} Pot\ T\ x_t^A \left(\frac{1}{2}\frac{T+1}{T} - \frac{t}{T}\right). \tag{6}$$

The proof of this corollary is relegated to Appendix A. Its first part says that the debt of group A is a decreasing function in the average rank of members of A. Their average debt is equal to a product of three terms, the share of Rosca participants who belong to A, s_A, the pot, and the number of months over which they borrow (or save) on average. As an implication, if the rounds in which group A wins pots average at half the Rosca's duration, the group's average financial position is just zero. Noticing that $\bar{t}^A$ is bounded by $s_A T/2$ from below and $T(1 - s_A/2)$ from above, it follows that the maximum debt capacity for group A according to equation 5 is

$$D^A_{\max} = s_A(1 - s_A)\frac{T\ Pot}{2}, \tag{7}$$

which shall serve as a reference for changes in D^A in our subsequent empirical analysis. An increase in the number of members belonging to A pushes back the average earliest round in which this group can win pots, implying that some members of A first have to save. Accordingly, the average maximum loan duration for members of A decreases. This is captured by the term $(1-s_A)$, which decreases the average debt capacity per member of group A. When s_A is small, on the other hand, A's maximum debt capacity roughly equals the group's membership share times half the Rosca turnover of $T * Pot$.

In the empirical analyses, our objective is to estimate average indebtedness of different professional groups by regression methods. The unit of observation is a single Rosca round (or auction), as laid out in equation 1. To arrive at a regression specification through which the average debt of group A in a Rosca can be estimated as a sample mean, we build on the second formula given in the corollary, equation 6, and derive our main dependent variable from the product $Pot\ T\ x_t^A\left(\frac{1}{2}\frac{T+1}{T} - \frac{t}{T}\right)$. When T is sufficiently large such that $\frac{T+1}{T}$ is close to one, a least-squares regression of $Pot\ T\ x_t^A\left(\frac{1}{2} - \frac{t}{T}\right)$ on a constant term will deliver precisely D^A as the point estimate. We will draw on this formulation in our empirical analysis and refer to $\frac{t}{T}$ as *relative round.*

3.3 Estimation strategy

We are interested in the change in debt (or conversely claims) held by different subgroups of Rosca participants in response to the tsunami. Most of our empirical analysis is guided by the formulas for debt spelled out in equation 5 and 6. Towards this, we will examine two objects of interest subsequently, first the empirical counterpart of x_t^A for different occupations, which we essentially view as a probability density on the domain of rounds (1 through T). The shape of these profiles tells us how early pots are obtained by different occupational groups. More specifically, we estimate the probabilities that a given occupational group wins a pot in different deciles of a Rosca, where we define a decile with respect to a Rosca's duration.[21] This concept of Rosca deciles, moreover, allows us to pool data from different Rosca denominations. Our difference-in-differences estimating equation

[21] To give an example, in a Rosca with 40 rounds, the first decile comprises rounds one through four, the second decile five through eight, and so on.

for the probability of group A winning a pot in decile τ is

$$\begin{aligned} x^A_{bdgt} &= \sum_{\tau=1}^{10}\left[\mathbb{1}\left\{\frac{\tau-1}{10}<\frac{t}{T_d}\leq\frac{\tau}{10}\right\}\left(\begin{array}{c}\alpha_\tau tsunami_b+\delta_\tau after_{bdgt}\\ +\beta_\tau tsunami_b\times after_{bdgt}\end{array}\right)\right] \\ &\quad +\rho_{bd}+\sum_{m=1}^{22}\gamma_m Month^m_{bdgt}+u_{bdgt}, \end{aligned} \tag{8}$$

where x^A_{bdgt} is an indicator for whether the pot in round t of Rosca group g of denomination d in branch b went to a member of group A. This is a straightforward extension of equation 1 to a situation of heterogenous treatment effects by Rosca decile.

Second, we will examine D^A as given in equation 6. We draw on estimating equation (1) to accommodate Roscas of different denominations and estimate the effect of the tsunami on the average debt of occupational group A by

$$x^A_{bdgt}\left(\frac{1}{2}-relround_{bdgt}\right)T_d Pot_d=\beta\ tsunami_b\times after_{bdgt}+\rho_{bd}+\sum_{m=1}^{22}\gamma_m Month^m_{bdgt}+u_{bdgt}, \tag{9}$$

where $relround_{bdgt}$ denotes the Rosca round t divided by the Rosca's duration T_d, and Pot_d the pot amount of denomination d. The parameters and other variables are as in equation 1.

We will now address two implementation issues arising in the context of our data. The first one is caused by an imbalance of relative Rosca rounds. This complication is due to our empirical design in which we only use Roscas that started before the tsunami (to rule out selection effects) and consider only auctions from 12 months before and the 10 months after the tsunami. According to the figures in Table 2, an average auction before the tsunami occurred towards the end of the first half, at a relative round of 0.47, while late rounds are more frequent after the tsunami, driving up the overall sample mean of the relative round to 0.55. This imbalance jeopardizes a consistent estimation of levels of and changes in debt through equation 9. To see this, consider a simple regression of $x^A_t(1/2-t/T)$ on a constant α and suppose observations from the Rosca's first half are oversampled relative to observations from the second half. Then the point estimate of α will be upward biased relative to D^A because positive observations from early rounds (where $t/T<1/2$) are more frequent than negative observations from late rounds (where $t/T>1/2$). To deal with this complication, we construct inverse probability weights, which give slightly larger (smaller) weights to late (early) relative to early (late) rounds before (after) the tsunami. We will refer to these weights as f-weights in the sequel. The technical details are relegated to Appendix B.

The second issue is that the Rosca organizer does not record the profession of all auction winners. While we are assured that the institutional investor is always recorded accurately by the organizer, among the remaining 66 percent of non-institutional Rosca members, the occupation is recorded for around two fifths of them; see Table 2. Missing occupational information is relatively rare in the first half of a Rosca but increases sharply towards the end, when the organizer faces less financial exposure (see Figure 2). To see how this jeopardizes consistent estimation of D^A as given in equation 5, consider again a simple regression of $x^A_t(1/2-t/T)$ on a constant α and suppose that self-employed Rosca participants win pots with the same likelihood in early, middle and late rounds. That is they are neither borrowers nor savers on average. Denoting the true x_t^A by x_t^{A*}, we have that $\Delta E[x_t^{A*}|t]/\Delta t = 0$ for all t and D^A as given in equation 5 equals zero. If, against this background, a drop in the organizer's screening effort over the Rosca cycle leads to a decrease of $E[x_t^A|t]$ in t, our estimation of debt will be upward biased because $\Delta E[x_t^A|t]/\Delta t < 0$. In addition, the organizer's effort to document borrowers' occupations could be affected by the tsunami. To explore this possibility, we take the incidence of missing occupational information of winners of auctions as dependent variable in equation 1. According to the results, which are set out in Table 3, the tsunami in fact increased the relative frequency of documented occupations in coastal branches. According to the point estimate in column 1, where the tsunami intensity is captured by the wave height, the incidence of winners with missing occupation information decreased by 1.3 percentage points per meter of wave height in response to the tsunami, which equals 3.8 percent of the sample mean of 34 percent. On the other hand, this effect is not statistically significant when accounting for the small number of clusters (wild cluster bootstrapped SE p-value: 0.18).

[Table 3 about here]

To deal with both of these complications, we construct an additional weight to compensate for missing occupation information. From our background interviews, it appears safe to assume that (i) the institutional investor is always accurately recorded and that (ii) the other occupations are screened at random. From these assumptions we construct an inverse probability weight, the g-weight, which corrects, first, for the organizer's lower effort to record occupations towards the end of a Rosca and, second, for the possibility of a change in this effort due to the tsunami. The technical details are relegated to Appendix B. The weight h, which corrects for both the imbalance over deciles and missing occupations is the product of the f-weight and the g-weight and will be used in all estimations of equation 8 and 9.

4 Results

4.1 Attrition, supply and market size

Although the size of funds and consequently supply within a Rosca is inelastic by design, Rosca groups could break down after the tsunami or individuals who had become Rosca members before the tsunami could leave the Roscas in 2005 before winning an auction due to, for example, liquidity shortages. As there is no prematurely terminated Rosca group in our sample, we focus on the second possibility and first address the tsunami's effect on membership attrition in groups that were formed before December 26, 2004. The organizing company has the policy that a Rosca member can give up her membership before winning an auction at a fee equal to three contributions. An exiting member is immediately replaced by the institutional investor, who is closely affiliated to the Rosca organizer. Exits of members are not explicitly recorded in our data. However, we can assess whether the incidence of the institutional investor winning an auction changes in response to the tsunami. We estimate equation 1 with a binary indicator equal to one if an auction is won by the institutional investor as the dependent variable. According to the results, which are set out in Panel A of Table

4, there is no change in the relative frequency of memberships held by the institutional investor in response to the tsunami.

Second, we address the tsunami's effect on the total supply of funds in all Roscas using three measures: a binary indicator for a new Rosca started based on the first auction date, the number of new Roscas started per branch per month, and the share of new Roscas started per branch per months relative to the total number of Roscas in this branch in the respective month.[22] We do not observe any change in the incidence of new Roscas started (Table 4, Panel B), in the number of new Roscas started (Table 4, Panel C) and the share of new Roscas started (Table 4, Panel D) in response to the tsunami.

[Table 4 about here]

Third, we study whether the tsunami affected the market size of Roscas in our sample using three measures: the number of Rosca auctions per branch per month, the number of Rosca participants per branch per month, and the sum of the amounts of all pots auctioned per branch per month. According to the results, which are set out in Table 4, Panels E through G, the point estimates are very small and statistically insignificant for all these variables. We conclude that in addition to the constant supply of funds within a given Rosca, the functioning and the volume of this segment of the credit market were unaffected by the tsunami. Any effect of the tsunami in our sample Roscas must therefore be due to the demand for funds in these credit networks.[23]

4.2 Flow of funds between occupational groups

The central econometric result of our analysis is foreshadowed by the occupational profiles set out in Figure 3. Clearly, self-employed participants in coastal branches win auctions much more often in the first three Rosca deciles after the tsunami. In comparison, the corresponding profiles are very similar across coastal and near-coastal branches before the tsunami as well as within near-coastal branches before and after the tsunami.

[Figure 3 about here]

We explore this pattern more formally by conducting regression analyses based on estimating equation (8). Because of the multitude of estimated coefficients we present these results graphically in Figure 4, which plots the estimated β coefficients decile by decile for each occupational group together with 99 percent confidence intervals for both tsunami intensity measures: a) run-up height and b) damage intensity. The pattern that emerges confirms the impression obtained from the raw data in Figure 3: self-employed members obtain earlier pots in response to the tsunami while wage-employed and not-employed members obtain earlier pots less and later pots more often. According to either

[22] For the first measure we use all 19,955 auction observation available to us and also consider Roscas that started after the tsunami. This allows us to compare the 175 Rosca groups that started in 2004 before December 26 to the 47 Rosca groups that started after the tsunami until August 2005.

[23] While the tsunami was a major natural disaster in India, its economic repercussions appear to have been only local. For the credit market, this is reflected by the fact that the tsunami does not appear to have affected India's domestic credit provided by the financial sector relative to GDP (59 percent in 2004, 60 percent in 2005; source: World Development Indicators).

panel, self-employed members' propensity to obtain a pot in the first and second decile in response to the tsunami increases by three (cluster robust SE p-value: 0.018; wild cluster bootstrapped SE p-value: 0.017) and two (cluster robust SE p-value: 0.017; wild cluster bootstrapped SE p-value: 0.069) percentage points per meter of wave height, respectively, which is a large increase relative to their projected average membership of 15 percent (see Table 5). Wage-employed members' propensity to obtain a pot in the first and second decile in response to the tsunami decreases by four (cluster robust SE p-value: 0.000; wild cluster bootstrapped SE p-value: 0.014) and three (cluster robust SE p-value: 0.009; wild cluster bootstrapped SE p-value: 0.027) percentage points per meter of wave height, respectively. All effects are very similar for the damage intensity measure. These findings are consistent with a heterogenous economic effect of the tsunami on different occupational groups, in particular on self-employed members.

[Figure 4 about here]
[Table 5 about here]

We proceed to analyze average debt of each occupational group according to equation 9. According to the results set out in column 1 of Table 6, debt of self-employed members increases significantly, by Rs. 21,918 per meter of wave height (cluster robust SE p-value: 0.000; wild cluster bootstrapped SE p-value: 0.001). Evaluated at the average wave height of 5.8 meters in the five coastal branches, this corresponds to Rs. 126,335 or US Dollar 2,886 of additional debt per Rosca. This finding is confirmed by the damage intensity measure, for which the point estimates are significant at the one percent level for cluster robust and wild cluster bootstrapped standard errors alike (Table 6, column 2).

Conversely, average claims of other occupational groups increase: wage-employed members' debt decreases by Rs. 11,156 per meter wave height, which corresponds to Rs. 64,303 on average (cluster robust SE p-value: 0.030; wild cluster bootstrapped SE p-value: 0.082), and the institutional investor's debt decreases by a similar amount, Rs. 12,107 per meter of wave height (cluster robust SE p-value: 0.016; wild cluster bootstrapped SE p-value: 0.387). For self-employed and wage-employed members, these effects are measured precisely and are confirmed by the damage intensity specification. The effect on the institutional investor's debt, on the other hand, is statistically insignificant with the bootstrap inference method and not confirmed by the damage intensity specification.

[Table 6 about here]

We now explore heterogeneous effects of the tsunami across different sub-segments of the Rosca financial market. Background interviews with the organizer suggested that self-employed individuals prefer Roscas with a larger pot size so that costly investments can be financed from Rosca funds. According to Table 5, in our sample Roscas, the share of self-employed participants is estimated at 19.7 percent in denominations with pots larger than the median pot value of Rs. 25,000 and only 6.9 percent in denominations with smaller pots.[24] Conversely, institutional investors are much less frequent in large Roscas, where they account for only twenty percent of participants (relative to

[24]The spearman rank correlation coefficient of the two variables *share of self-employed* and *pot size* is 0.42 (p-value < 0.001).

48 percent in small Roscas). When we carry out the debt estimations separately by pot size, we find that the re-allocation of funds from wage-employed and institutional investors to self-employed participants is driven exclusively by Roscas with large pots, in which entrepreneurs gain Rs. 32,778 per meter of wave height (Column 4 of Table 6). In contrast, all point estimates are small and statistically insignificant at conventional levels in the sub-sample of Roscas with small pots. We conclude that the tsunami affected financial intermediation only in Roscas which are especially popular among entrepreneurs. This pattern is suggestive of a scenario where the re-allocation of funds is driven primarily by a demand hike among entrepreneurs rather than a change in demand among any of the other participant groups.

To put the estimated changes in debt into perspective, we first calculate each occupational group's average debt for all observations in 2004, before the tsunami. According to the 'Debt at baseline' entries in Table 6, only the institutional investor holds significant debt at baseline, worth 71,400 Rs. per group, while none of the other three occupational groups deviates significantly from a neutral financial position; their estimated average debt is small and not significantly different from zero.[25] For the self-employed, the estimated increase in debt per Rosca of Rs. 126,335 corresponds to six percent of the average turnover of a sample Rosca of Rs. 2.08 million, and with an estimated average of 5.5 self-employed participants per group, each of them holds additional debt of Rs. 23,049 or US Dollar 526. This amount equals 75% of India's per capita GDP at the time (not purchasing-power-parity adjusted) and is equivalent to forty percent of an average Rosca pot or 14.9 monthly contributions. Given the total number of 490 Roscas in the five coastal branches, this amounts to additional debt of Rs. 61.9 million or US Dollar 1.4 million. Another way to look at entrepreneurs' debt increase is to relate the point estimates in Table 6 to their borrowing capacity, as stated in (7). According to this formula and using the figures in Tables 2 and 5, their borrowing capacity stands at Rs. 138,593 per group on average. Hence the additional borrowings per meter of wave height of Rs. 21,918 equal sixteen percent of their debt capacity and the estimated average effect for the five coastal branches of Rs. 126,335 equals more than 80 percent of the maximum they could borrow from the Roscas in our sample. Similarly, for the sub-sample of large Roscas, the additional borrowings per meter of wave height of Rs. 32,778 equal twelve percent of their debt capacity of Rs. 274,704 in these Roscas. Given that wage-employed participants are much more frequent in small and large Roscas alike, their estimated increase in average claims in large Roscas amounts to only 3.7 percent of their maximum savings capacity per meter of wave height. In contrast, for the institutional investor the estimated effect of Rs. 18,289 (column 4 of Table 6) per meter of wave height is bigger in relative terms, 6.6 percent of his debt capacity in these groups, because he holds substantially fewer memberships in large Roscas than wage-employed participants (20 relative to 48 percent; see Table 5).

To summarize, these analyses show that substantial funds were channeled to self-employed participants in response to the tsunami. The source of these funds are, to similar extents, wage-employed individuals and the institutional investor. Moreover, this re-allocation occurs solely in large Roscas, which are especially popular with entrepreneurs. These patterns suggest that the observed

[25] This pattern is in line with Eeckhout and Munshi (2010), who also use data from a chit fund company in Tamil Nadu covering the years 1993 and 1994 (i.e. prior to the tsunami). The point of departure of their analysis of matching of different groups of members in Roscas in response to a regulatory shock is that 'corporate subscribers' (whom we call 'insitutional investor') participate in chit funds primarily with a borrowing motive.

re-allocation of funds is primarily due to a hike in demand among entrepreneurs, which is driven by their double affectedness and their need for funds for replacement investments - consistent with the findings of De Mel et al. (2012) on returns to capital in the aftermath of the tsunami.

4.3 Price of credit

We now assess the changes in the price of credit in response to the tsunami. We focus on the relative winning bid, the nominal winning bid divided by the amount in the pot, as outcome variable, which allows us to pool financial data from Roscas of different denominations. Table 7 contains the results, separately for all auctions and by occupational group. According to the point estimate in column 1, winning bids increased by 0.26 percentage points per meter of wave height (cluster robust SE p-value: 0.020; wild cluster bootstrapped SE p-value: 0.049), which implies an average increase of 1.49 percentage points for the five coastal branches. Relative to the sample mean of 17.36 percentage points, this corresponds to increases of 1.5 percent and 8.6 percent, respectively (Table 7, column 1). According to the disaggregated analyses by occupational group, this increase is entirely driven by auctions won by self-employed participants and the institutional investor. While the effect for the self-employed is imprecisely estimated, it cannot be distinguished statistically from the institutional investor's coefficient.

[Table 7 about here]

In line with our findings regarding financial flows, this pattern is consistent with a demand hike among entrepreneurs and only negligible demand changes, if any, among the other occupations. The institutional investor's seemingly contradictory pattern of winning later pots while making higher bids is consistent with the strategic behavior of a monopolistic arbitrager: the theoretical analysis of Klonner and Rai (2010) yields that optimal monopolistic arbitrage across locations mandates higher bids and higher ranks (that is later pots) of the arbitrager in locations with greater other demand.[26]

The instantaneous price increase and the previously demonstrated reallocation of funds illustrate the simultaneous flexibility and rigidity of chit funds as a 'middle-rung' non-market institution in an exemplary fashion. On the one hand, the concurrent auction allotment mechanism permits an instantaneous rechanneling of funds to participants with greater need, even in groups that had formed before the disaster. On the other hand, the price increase documents the fragmented nature of the chit fund segment of the financial market: among all participants in the around eighty branches operated by the organizer in Tamil Nadu, the group of entrepreneurs with tsunami damages would be very small and no significant change in market prices would be expected if aggregate demand and supply in different locations were pooled.

4.4 Loan characteristics and default

It is a possibility that the Rosca organizer anticipated problems by winners of auctions to continue their contributions in response to the tsunami and adjusted screening practices and loan securitization

[26] In contrast, competitive arbitrage would imply equal bids and only higher ranks of the arbitrager in locations with greater other demand. Since the institutional investor is a single firm, which entertains a close business relationship with the organizer, who in turn puts up entry barriers for other commercial investors, we think that monopolistic arbitrage is a realistic scenario in the Roscas considered here.

accordingly. If this is in turn anticipated by Rosca members, such changes in loan terms and screening by the lender could result in changes in occupational patterns of ranks and winning bids. To assess this possibility we test various characteristics of the loans in our sample, in particular measures of screening, securitization and default.

Applying our difference-in-differences framework, we test whether the Rosca organizer's screening effort by collecting occupation and income information of auction winners changes in response to the tsunami. We consider as dependent variables in equation 1 two indicators equal to one if the lender screens the borrower by recording her occupation (Table 8, Panel A) or income (Panel B), respectively. According to Panels A and B of Table 8, columns 1, there are moderate, albeit imprecisely estimated increases in both occupation (cluster robust SE p-value: 0.022; wild cluster bootstrapped SE p-value: 0.181) and income screening (cluster robust SE p-value: 0.031; wild cluster bootstrapped SE p-value: 0.230) for the run-up height measure. They cannot be confirmed for the damage intensity measure in column 2.

[Table 8 about here]

Second, we look at the incidence and the number of cosigners. We estimate equation 1 using a binary indicator equal to one if any cosigner is provided and the number of cosigners as dependent variables. We find a change in neither the incidence of providing cosigners nor the number of cosigners (Table 8, Panel C and D in columns 1 and 2).

Third, we explore whether enforcement activities or defaults increased in response to the tsunami. Our measures of default are based on the cumulative amount owed but not repaid at the time of data collection in November 2005: first, an indicator variable for being in arrear and, second, the amount in arrear relative to the pot. In addition, we consider an indicator for legal measures taken against the borrower. There is no change in the arrear incidence and a small and imprecisely estimated increase in the amount (cluster robust SE p-value: 0.072; wild cluster bootstrapped SE p-value: 0.148) for the run-up height measure (Table 8, Panel E, and F in columns 3 and 4). On the other hand, there is only a small and insignificant negative effect on legal enforcement. Hence, we conclude that loan securitization, enforcement and defaults did not change in response to the tsunami. If anything, screening of borrowers increased somewhat.

5 Robustness checks

5.1 Placebo experiment

Different time trends across coastal and near-coastal branches absent the tsunami jeopardize the interpretation of our difference-in-differences estimation results as causal effects. To assess whether different time trends are an issue in our context, we conduct a placebo experiment. We keep the same specification as in equation 9 but use data on auctions entirely before the tsunami from 2003 to 2004. The assignment of tsunami intensity levels to branches remains the same. We create an artificial event of a *pseudo-tsunami* on December 26 in 2003, exactly one year before the actual Indian Ocean tsunami. All observations from January 1 to December 26, 2003 are classified as *before pseudo-tsunami* and all observations from December 27, 2003 to December 25, 2004 as *after pseudo-tsunami*. If time trends in coastal and near-coastal locations are parallel, we do not expect any treatment effects in such a placebo estimation as no disaster took place at the time of the artificially created event.

[Table 9 about here]

The data set used in the placebo experiment contains 19,678 auctions from January 2003 to December 2004 (Appendix C, Table C.2). The geophysical data used in the placebo experiment is the same as in the original analysis with the same tsunami intensity measures. All point estimates in these placebo estimations set out in Table 9 are small relative to the effects in our main debt estimations. They are, moreover, statistically insignificant for the groups of self-employed, wage-employed, and institutional investors. It is only for the group of not-employed members and the sample of all Roscas, where we obtain some small positive effects that are statistically significant at the ten percent level with the bootstrap inference methodology. When we disaggregate by pot size, none of the effects is statistically significant at conventional levels. Overall, these results give us confidence that the results obtained in our main analysis are not driven by systematically different trends in the data.

5.2 Definition of coastal branches

We have restricted our sample to the 14 branches located within 25 kilometers of the coastline. As a robustness check, we now consider variations of this rule. First, we vary the distance to the coastline and consider cutoffs of 15 and 20 rather than 25 kilometers. This reduces the number of branches to 11 and 12, respectively, and yields a more balanced number of coastal and near-coastal branches. On the other hand, this choice comes at the cost of an even smaller number of clusters (Table 10, columns 2 (7) and 3 (8) for the run-up height (damage intensity) tsunami intensity measure). Second, we increase the distance to 50 kilometers, which increases the number of branches to 25 (Table 10, column 4 (9)). Third, we remove all branches that are more than five and less than fifteen kilometers away from the coastline, eight branches in total (Table 10, column 5 (10)). By excluding near-coastal branches, we assess the possibility of spillover effects from coastal to near-coastal locations.

[Table 10 about here]

Table 10 sets out the results for our main definition of coastal branches (columns 1 (6)) and all variations listed above. We obtain very similar point estimates and significance levels for debt in all variations. Effect sizes for the self-employed participants are slightly larger when accounting for spillover effects (column 5 in comparison to 1), consistent with a scenario where near-coastal locations were also somewhat economically affected by the tsunami even though the waves did not reach them physically. All in all, our results are remarkably robust to alternative definitions of the sample.

6 Conclusion

In this study, we investigate responses of local credit networks to the December 2004 Indian Ocean tsunami. We apply a difference-in-differences approach using geophysical data on the local severity of the tsunami and detailed financial data from semi-formal Roscas in Tamil Nadu. Based on these local credit networks with inelastic credit supply in the short run, we analyze how credit flows between occupational groups, the price of credit, loan securitization and default change in response to the natural disaster.

We find a significant increase in the competition for loans on the demand side, while the supply of funds remains robust and stable. Further, we find a large increase in credit flows to Rosca participants who are entrepreneurs. These funds are provided by coresident wage-employed participants and a commercial investor, who arbitrages across Roscas in different locations and hence provides some financial intermediation across space. These findings demonstrate the responsiveness of these credit networks to the large economic shock. They are, moreover, consistent with previous studies of the tsunami's economic consequences. The immediate response in the credit networks that we have studied is facilitated by the flexible auction allocation mechanism, a non-market element of bidding Roscas. In contrast to the wide-spread scepticism regarding the potential of traditional, local institutions for mitigating the effects of covariate shocks, our results suggest that Roscas played an important role for coping with this large negative shock. In this connection, both local as well as inter-local financial intermediation facilitated by the institution studied provided urgently-needed funds to small entrepreneurs.

We propose to also interpret these findings as indirect evidence for the unavailability of other forms of relief. Relief aid and rehabilitation efforts were high given the severe destructions the December 2004 tsunami caused. The Government of Tamil Nadu and the Indian Government strived to deal with the consequences of the tsunami mainly without foreign aid, although relief work of NGOs and international agencies and institutions was accepted. While relief packages were sanctioned to reconstruct infrastructure and residences and to replace productive assets, the flow of those aid payments arrived with a substantial time lag. For example, the *Tsunami Emergency Assistance Project (TEAP)* started over four months after the tsunami, in April 2005 (Tamil Nadu Government (2005a)). A substantial number of government orders were released nearly one year after the tsunami. This suggests that semi-formal credit studied here and official aid are substitutes as disaster coping mechanisms rather than complements.

Our findings highlight the role of traditional, non-market, network-based economic institutions for dealing with economic risks when markets and governments do not or cannot react quickly. They challenge the common view that local mutual insurance schemes fail to insure covariate shocks. Further research on the exact channels how funds are put to work in the recovery process of enterprises would be needed to further understand the full potential of credit as a coping mechanism for covariate shocks. In addition, research exploring how local financial institutions and networks could be leveraged to efficiently channel external relief aid to households and enterprises seems a worthwhile avenue for future research and policy.

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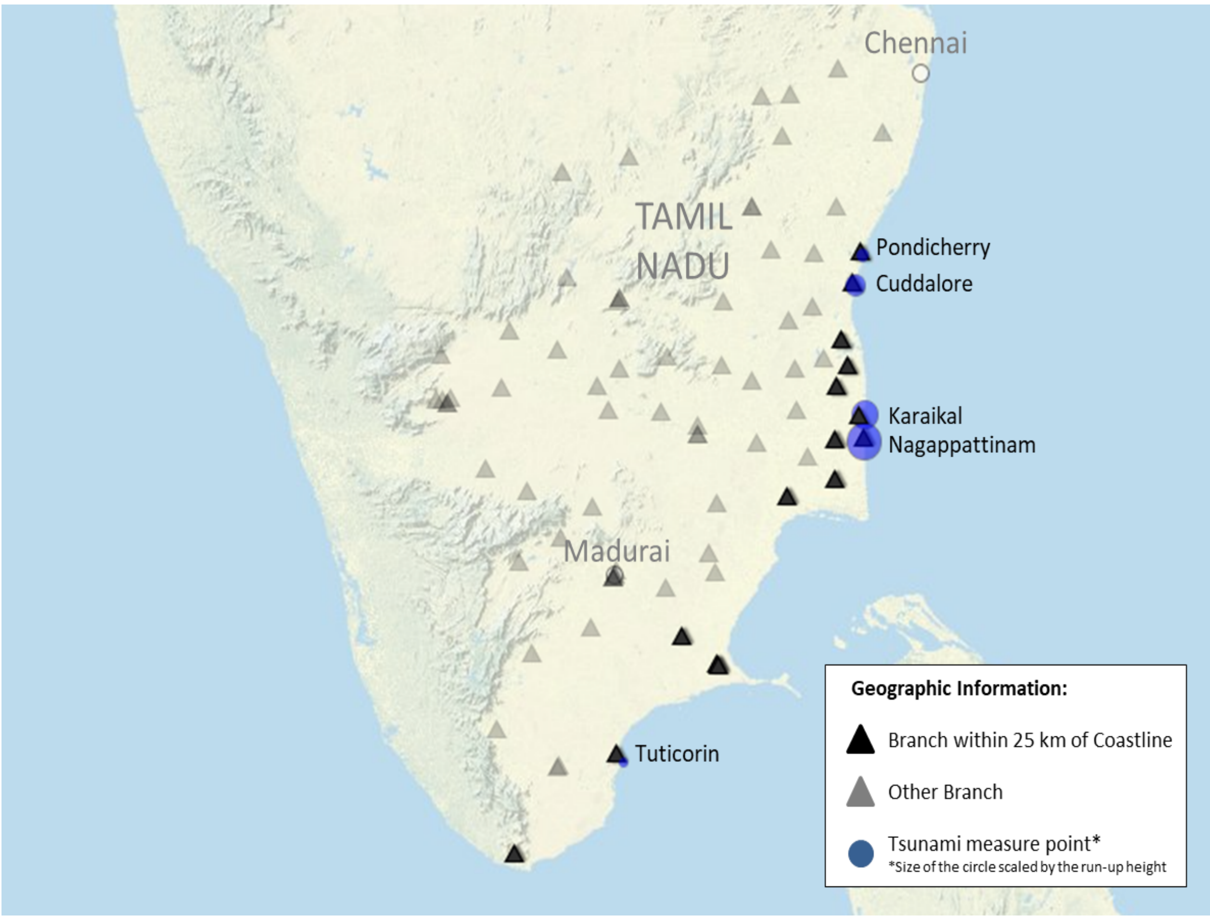
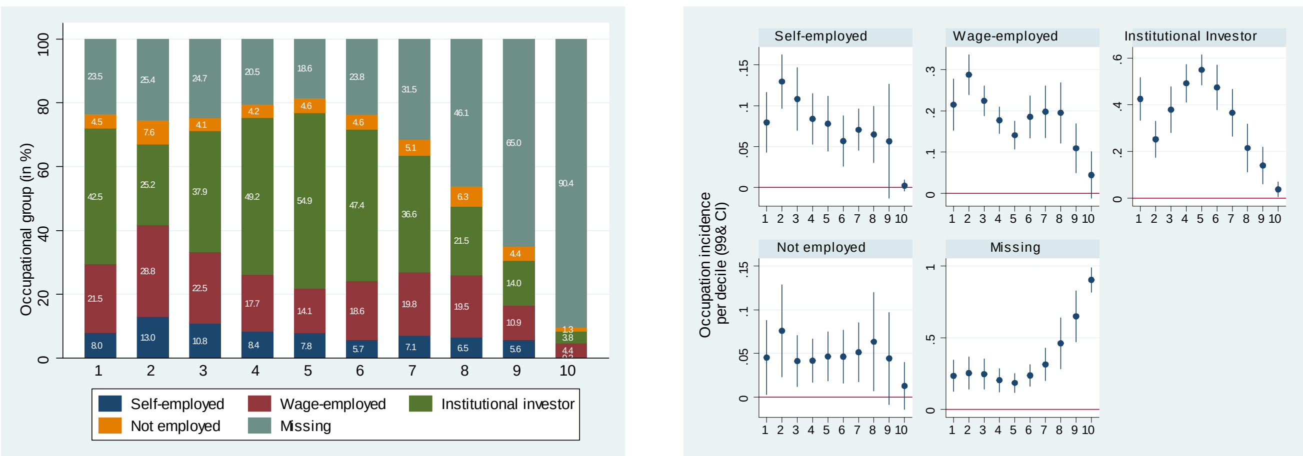
7 Figures

Figure 1: Tsunami intensity and branch locations



Notes: The map depicts all branches of the organizer in Tamil Nadu (except for the state capital Chennai). The branch names refer to coastal branches.

Figure 2: Recorded occupations of borrowers at baseline (in 2004), by Rosca decile



(a) Occupational composition of borrowers

(b) Relative frequency of occupations

Figure 3: Relative frequency of self-employed Rosca participants

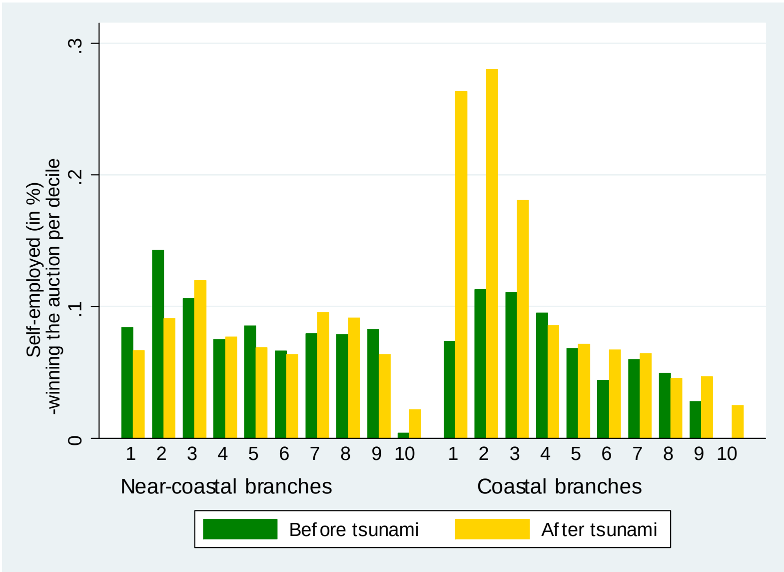
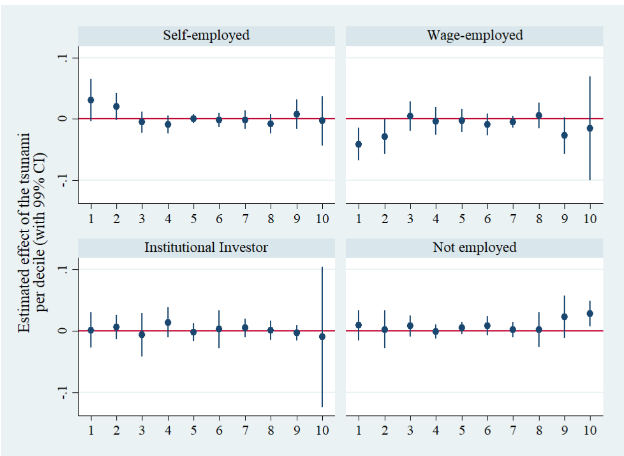
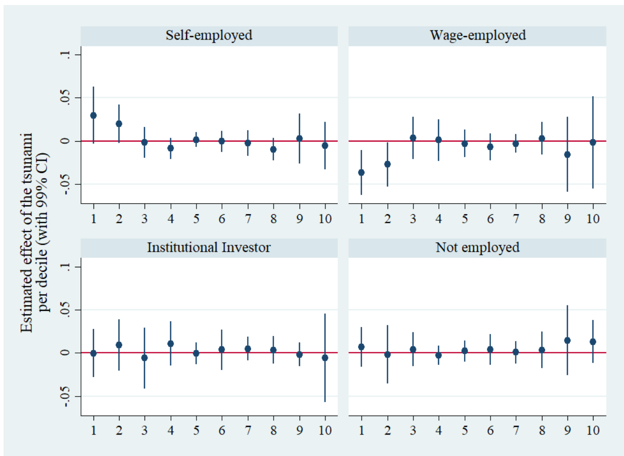


Figure 4: Changes in the relative frequency of occupations caused by the tsunami, by Rosca decile



(a) run-up height



(b) damage intensity

Notes: Plots depict the estimated β-coefficients of estimating equation (8) for the different occupational groups. Dependent variable: Dummy for occupational group A if auction is won by group A, where A equals 'self-employed', 'wage-employed', 'institutional investor' or 'not employed' in the different panels. Each dot represents a point estimate and the surrounding bar the respective 99% confidence interval. Data from Rosca auctions in 14 branches from January 2004 to October 2005. Month-of-auction and branch-denomination fixed effects included in all estimations. Standard errors clustered at the branch level. Weighted OLS: h-weights included in all estimations.

8 Tables

TABLE 1: Descriptive statistics: Geophysical data

	Mean	Standard deviation	Minimum	Maximum
	(1)	(2)	(3)	(4)
All branches (19,594 observations)				
Run-up height (in meters)	2.591	3.430	0	11
Damage intensity	3.578	4.063	0	10
Near-coastal branches (10,786 observations)				
Run-up height (in meters)	0	0	0	0
Damage intensity	0	0	0	0
Coastal branches (8,808 observations)				
Run-up height (in meters)	5.764	2.807	3	11
Damage intensity	7.960	1.358	6.5	10

Notes: All geophysical data is based on tsunami survey measure points of the Indian Institute of Technology Roorkee for the five coastal branches. Run-up height: maximum height of water observed above a reference sea level in meters. Damage intensity: I) not felt, II) scarcely felt, III) weak, IV) largely observed, V) strong, VI) slightly damaging, VII) damaging, VIII) heavy damaging, IX) destructive, X) very destructive, XI) devastating, and XII) completely devastating.

Table 2: Descriptive statistics: Financial data

	All auctions			Auctions before tsunami		
	All branches	Min	Max	Near-coastal branches	Coastal branches	p-value F-test
	(1)	(2)	(3)	(4)	(5)	(6)
Duration (in months)	36.54	25	60	35.99	35.59	0.631
	(6.87)			(6.60)	(7.62)	
Monthly contribution (in Rs.)	1,546	200	30,000	1,453	1,663	0.120
	(2,613)			(2,401)	(2,922)	
Pot (in Rs.)	56,955	10,000	1,000,000	52,263	59,769	0.120
	(100,243)			(89,049)	(108,882)	
Turnover (in 1,000 Rs.)	2,174	250	50,000	1,940	2,248	0.109
	(4,079)			(3,468)	(4,348)	
Winning bid (in Rs.)	11,329	500	300,000	12,181	13,319	0.401
	(24,356)			(24,533)	(27,183)	
Relative winning bid (in %)	17.363	5	40	20.386	19.932	0.557
	(11.342)			(11.430)	(11.854)	
Round of auction	19.667	1	47	16.293	16.399	0.723
	(9.100)			(8.041)	(7.924)	
Relative round of auction	0.548	0	1	0.465	0.478	0.270
	(0.248)			(0.238)	(0.242)	
Income recorded by lender*	0.784	0	1	0.872	0.788	0.278
	(0.411)			0.334	0.409	
Occupation recorded by lender	0.656	0	1	0.739	0.626	0.057
	(0.475)			(0.439)	(0.483)	
Cosigner (incidence)*	0.543	0	1	0.665	0.593	0.177
	(0.498)			(0.472)	(0.491)	
Number of cosigners*	1.106	0	9	1.450	1.256	0.081
	(1.250)			(1.306)	(1.287)	
Arrear (incidence)*	0.444	0	1	0.579	0.536	0.226
	(0.497)			(0.494)	(0.499)	
Arrear amount (relative to pot)*	0.033	0	1	0.048	0.048	0.971
	(0.068)			(0.082)	(0.085)	
Legal enforcement*	0.086	0	1	0.108	0.197	0.186
	(0.280)			(0.311)	(0.398)	
Occupation of auction winners						
Self-employed	0.074	0	1	0.084	0.069	0.290
	(0.262)			(0.278)	(0.253)	
Wage-employed	0.192	0	1	0.192	0.175	0.425
	(0.394)			(0.394)	(0.380)	
Institutional investor	0.339	0	1	0.407	0.346	0.181
	(0.473)			(0.491)	(0.476)	
Not-employed	0.051	0	1	0.056	0.038	0.373
	(0.221)			(0.229)	(0.192)	
Occupation not recorded by lender	0.344	0	1	0.261	0.372	0.054
	(0.475)			(0.397)	(0.483)	
Number of observations	19,594			6,192	5,133	

Notes: Table contains means, standard deviations in parentheses. Standard errors clustered at the branch level for the p-value of F-test of differences in means in column 6. Data from Rosca auctions in 14 branches from January 2004 to October 2005.
*Only observations from recipients of pots other than the institutional investor (12,960 auctions).

Table 3: Recording of occupations by the Rosca organizer

Dependent Variable: Missing occupation (dummy)	Run-up Height	Damage Intensity
	(1)	(2)
Tsunami x after tsunami	-0.013**	-0.009
	(0.005)	(0.006)
Observations	19594	19594
R-squared	0.151	0.150
P-value - bootstrapped S.E.	0.181	0.232
Confidence Interval (95%)	[-0.025;0.008]	[-0.023;0.008]
Mean of dependent variable	0.344	

Notes: Dependent variable: Dummy variable for whether the occupation of the winner of an auction is recorded. Weighted OLS: f-weights included. Data from Rosca auctions in 14 branches from January 2004 to October 2005. Month-of-auction and branch-denomination fixed effects included in all specifications. Standard errors clustered at the branch level in parentheses; p-values and confidence intervals for wild cluster-bootstrapped standard errors clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: Market characteristics: Attrition in Roscas and market size

	Run-up Height (1)	Damage Intensity (2)		Run-up Height (3)	Damage Intensity (4)
Attrition			**Market size**		
Panel A: Institutional investor (incidence)	Mean:	0.330	*Panel E: Number of Rosca auctions*	Mean:	64.789
Tsunami x after tsunami	0.004	0.003	Tsunami x after tsunami	0.007	-0.382
	(0.003)	(0.003)		(0.580)	(0.611)
P-value - bootstrapped S.E.	0.217	0.446	P-value - bootstrapped S.E.	0.99	0.536
Confidence Interval (95%)	[-0.006;0.014]	[-0.005;0.010]	Confidence Interval (95%)	[-3.049;1.074]	[-2.237;0.852]
Observations	19594	19594	Observations	308	308
R-squared	0.180	0.180	R-squared	0.981	0.982
Supply					
Panel B: New Rosca started (incidence)	Mean:	0.011	*Panel F: Number of Rosca participants*	Mean:	2366.023
Tsunami x after tsunami	0.000	0.000	Tsunami x after tsunami	3.741	-7.333
	(0.000)	(0.000)		(16.547)	(17.488)
P-value - bootstrapped S.E.	0.991	0.588	P-value - bootstrapped S.E.	0.827	0.671
Confidence Interval (95%)	[-0.002;0.002]	[-0.001;0.001]	Confidence Interval (95%)	[-77.3;38.3]	[-56.8;28.5]
Observations	19955	19955	Observations	308	308
R-squared	0.028	0.028	R-squared	0.986	0.986
Panel C: Number of new Roscas started	Mean:	0.721	*Panel G: Pot value (in 1000 Rs.)*	Mean:	3680.162
Tsunami x after tsunami	-0.015	-0.018	Tsunami x after tsunami	32.719	-4.81
	(0.023)	(0.021)		(53.041)	(52.233)
P-value - bootstrapped S.E.	0.528	0.386	P-value - bootstrapped S.E.	0.683	0.928
Confidence Interval (95%)	[-0.096,0.039]	[-0.066,0.026]	Confidence Interval (95%)	[-198.3;110.0]	[-1387;102.8]
Observations	308	308	Observations	308	308
R-squared	0.330	0.330	R-squared	0.97	0.969
Panel D: Share of new Roscas started	Mean:	0.012			
Tsunami x after tsunami	-0.000	-0.000			
	(0.001)	(0.001)			
P-value - bootstrapped S.E.	0.802	0.840			
Confidence Interval (95%)	[-0.003;0.001]	[-0.002;0.001]			
Observations	308	308			
R-squared	0.308	0.307			

Notes: Dependent variables in Panels C through G are aggregated per branch per month. Data from Rosca auctions in 14 branches from January 2004 to October 2005. Data in Panel B also includes Roscas that started after the tsunami on December 26, 2004 that are not considered in the other analyses. Month-of-auction and branch-denomination fixed effects included in Panels A and B. Month-of-auction and branch fixed effects included in Panels C through G. Standard errors clustered at the branch level in parentheses; p-values and confidence intervals for wild cluster-bootstrapped standard errors clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Occupations of Rosca participants (relative frequencies)

	Self-employed (1)	Wage-employed (2)	Institutional investor (3)	Not employed (4)
All Roscas				
Estimated occupation share	0.150***	0.439***	0.302***	0.108***
(Constant)	(0.015)	(0.033)	(0.023)	(0.017)
Observations	12855	12855	12855	12855
R-squared	0.000	0.000	0.000	0.000
Small pot size Roscas				
Estimated occupation share	0.069***	0.365***	0.477***	0.089***
(Constant)	(0.012)	(0.056)	(0.049)	(0.020)
Observations	5730	5730	5730	5730
R-squared	0.000	0.000	0.000	0.000
Large pot size Roscas				
Estimated occupation share	0.197***	0.482***	0.202***	0.119***
(Constant)	(0.017)	(0.026)	(0.015)	(0.017)
Observations	7125	7125	7125	7125
R-squared	0.000	0.000	0.000	0.000

Notes: Dependent variables: Dummy for occupational group j if auction is won by group j. Sample includes observations for which the occupation is recorded. Weighted OLS: h-weights included. Data from Rosca auctions in 14 branches from January 2004 to October 2005. The sub-sample with small pot sizes includes Roscas where the pot is worth Rs. 25,000 or less. The sub-sample with large pot sizes includes Roscas where the pot is worth more than Rs. 25,000. Month-of-auction and branch-denomination fixed effects included in all specifications. Standard errors clustered at the branch level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Change in debt by occupational group

	Run-up Height	Damage Intensity	Run-up Height		Damage Intensity	
Dependent variable: Debt (in 1,000 Rs.)			small pot size	large pot size	small pot size	large pot size
	(1)	(2)	(3)	(4)	(5)	(6)
Occupation: Self-employed	Debt at baseline:	9.744				
		(10.535)				
Tsunami x after tsunami	21.918***	19.470***	-0.061	32.778***	0.277	29.094***
	(3.141)	(4.852)	(0.505)	(4.531)	(0.509)	(6.861)
P-value - bootstrapped S.E.	0.001	0.001	0.912	0.000	0.622	0.000
Confidence Interval (95%)	[8.999;33.544]	[5.301;29.350]	[-1.130;2.859]	[14.012;48.107]	[-0.702;1.730]	[9.159;43.253]
R-squared	0.539	0.539	0.293	0.542	0.294	0.542
Occupation: Wage-employed	Debt at baseline:	21.477				
		(27.783)				
Tsunami x after tsunami	-11.156**	-11.232***	-1.902	-16.075**	-2.185*	-16.147**
	(4.572)	(3.669)	(1.109)	(6.195)	(1.203)	(5.994)
P-value - bootstrapped S.E.	0.082	0.026	0.160	0.084	0.087	0.047
Confidence Interval (95%)	[-27.136;5.280]	[-20.119;-2.388]	[-7.150;1.562]	[-37.584;9.814]	[-5.336;0.570]	[-30.217;-0.383]
R-squared	0.549	0.549	0.322	0.554	0.323	0.554
Occupation: Institutional investor	Debt at baseline:	71.421***				
		(14.270)				
Tsunami x after tsunami	-12.107**	-6.772	0.126	-18.289**	0.334	-10.154
	(4.356)	(5.925)	(0.622)	(7.209)	(0.785)	(9.218)
P-value - bootstrapped S.E.	0.387	0.462	0.836	0.387	0.684	0.471
Confidence Interval (95%)	[-18.614;13.142]	[-19.069;9.270]	[-2.330;1.982]	[-29.000;21.694]	[-1.751;2.298]	[-29.811;15.103]
R-squared	0.138	0.138	0.191	0.136	0.191	0.135
Occupation: Not employed	Debt at baseline:	-7.500				
		(13.057)				
Tsunami x after tsunami	1.219	1.365	-1.707*	2.548	-0.927	2.567
	(5.692)	(4.259)	(0.889)	(8.261)	(0.974)	(6.131)
P-value - bootstrapped S.E.	0.752	0.761	0.646	0.705	0.636	0.737
Confidence Interval (95%)	[-6.323;21.242]	[-6.098;14.428]	[-3.146;1.746]	[-8.714;28.941]	[-2.934;1.328]	[-8.252;20.763]
R-squared	0.158	0.158	0.199	0.163	0.196	0.163
Observations	12855	12855	5730	7125	5730	7125

Notes: Dependent Variable: Occupational group's debt: (incidence of winning the auction)*(0.5 - relative round of auction)*pot value. Weighted OLS: h-weights included. Data from Rosca auctions in 14 branches from January 2004 to October 2005. Month-of-auction and branch-denomination fixed effects included in all specifications. Standard errors clustered at the branch level in parentheses; p-values and confidence intervals for wild cluster-bootstrapped standard errors clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: Price of credit

	Run-up Height (1)	Damage Intensity (2)
Winning bid - All auctions		
Tsunami x after tsunami	0.260**	0.195*
	(0.098)	(0.097)
P-value - bootstrapped S.E.	0.049	0.110
Confidence Interval (95%)	[0.001;0.623]	[-0.071;0.441]
Observations	19594	19594
R-squared	0.455	0.455
Winning bid - By occupation		
Occupation: Self-employed		
Tsunami x after tsunami	0.218	0.276
	(0.265)	(0.224)
P-value - bootstrapped S.E.	0.451	0.259
Confidence Interval (95%)	[-0.222;1.066]	[-0.186;0.800]
Observations	1457	1457
R-squared	0.497	0.498
Occupation: Wage-employed		
Tsunami x after tsunami	-0.011	-0.064
	(0.099)	(0.106)
P-value - bootstrapped S.E.	0.910	0.574
Confidence Interval (95%)	[-0.581;0.262]	[-0.344;0.153]
Observations	3756	3756
R-squared	0.538	0.538
Occupation: Institutional investor		
Tsunami x after tsunami	0.267***	0.256***
	(0.079)	(0.078)
P-value - bootstrapped S.E.	0.072	0.026
Confidence Interval (95%)	[-0.027;0.581]	[0.039;0.408]
Observations	6634	6634
R-squared	0.319	0.319
Occupation: Not employed		
Tsunami x after tsunami	-0.039	-0.126
	(0.201)	(0.220)
P-value - bootstrapped S.E.	0.833	0.549
Confidence Interval (95%)	[-0.756;0.951]	[-0.673;0.424]
Observations	1008	1008
R-squared	0.599	0.599

Notes: Dependent Variable: Relative winning bid (percentage of the winning bid in the pot value of a Rosca). Data from Rosca auctions in 14 branches from January 2004 to October 2005. Month-of-auction and branch-denomination fixed effects included in all specifications. Standard errors clustered at the branch level in parentheses; p-values and confidence intervals for wild cluster-bootstrapped standard errors clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Screening, loan securitization and default

	Run-up Height (1)	Damage Intensity (2)		Run-up Height (3)	Damage Intensity (4)
Screening			**Default**		
Panel A: Occupation recorded by lender			*Panel E: Arrear (incidence)*		
Tsunami x after tsunami	0.013**	0.009	Tsunami x after tsunami	0.004	0.003
	(0.005)	(0.006)		(0.004)	(0.004)
P-value - bootstrapped S.E.	0.181	0.232	P-value - bootstrapped S.E.	0.258	0.559
Confidence Interval (95%)	[-0.008;0.025]	[-0.008;0.023]	Confidence Interval (95%)	[-0.003;0.019]	[-0.005;0.013]
Observations	19594	19594	Observations	12960	12960
R-squared	0.151	0.150	R-squared	0.136	0.136
Panel B: Income recorded by lender			*Panel F: Arrear amount (relative to pot)*		
Tsunami x after tsunami	0.012**	0.007	Tsunami x after tsunami	0.001*	0.001
	(0.005)	(0.006)		(0.001)	(0.001)
P-value - bootstrapped S.E.	0.230	0.319	P-value - bootstrapped S.E.	0.148	0.342
Confidence Interval (95%)	[-0.010;0.020]	[-0.009;0.020]	Confidence Interval (95%)	[-0.002;0.003]	[-0.001;0.002]
Observations	12960	12960	Observations	12960	12960
R-squared	0.266	0.265	R-squared	0.131	0.131
Loan securitization					
Panel C: Cosigner (incidence)			*Panel G: Legal enforcement (incidence)*		
Tsunami x after tsunami	0.003	0.001	Tsunami x after tsunami	-0.005	-0.007
	(0.004)	(0.004)		(0.006)	(0.006)
P-value - bootstrapped S.E.	0.452	0.757	P-value - bootstrapped S.E.	0.416	0.358
Confidence Interval (95%)	[-0.010;0.018]	[-0.008;0.011]	Confidence Interval (95%)	[-0.033;0.005]	[-0.024;0.008]
Observations	12960	12960	Observations	12960	12960
R-squared	0.241	0.241	R-squared	0.182	0.183
Panel D: Number of cosigners					
Tsunami x after tsunami	-0.003	-0.006			
	(0.012)	(0.011)			
P-value - bootstrapped S.E.	0.839	0.608			
Confidence Interval (95%)	[-0.039;0.037]	[-0.031;0.022]			
Observations	12960	12960			
R-squared	0.349	0.349			

Notes: Data from Rosca auctions in 14 branches from January 2004 to October 2005. For Panels B-G, the sample is restricted to recipients of pots other than the institutional investor. Month-of-auction and branch-denomination fixed effects included in all specifications. Standard errors clustered at the branch level in parentheses; p-values and confidence intervals for wild cluster-bootstrapped standard errors clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Change in debt by occupational group, placebo-experiment (2003 and 2004)

	Run-up Height	Damage Intensity	Run-up Height		Damage Intensity	
Dependent variable: Debt (in 1,000 Rs.)			small pot size	large pot size	small pot size	large pot size
	(1)	(2)	(3)	(4)	(5)	(6)
Occupation: Self-employed						
Pseudo-tsunami x after pseudo-tsunami	-6.176	-5.653*	0.230	-9.994	0.383	-9.200
	(3.948)	(3.032)	(0.517)	(7.561)	(0.473)	(5.666)
P-value - bootstrapped S.E.	0.415	0.108	0.687	0.456	0.485	0.153
Confidence Interval (95%)	[-13.235;8.911]	[-12.210;1.770]	[-1.445;2.338]	[-21.976;15.501]	[-0.705;1.598]	[-22.578;3.981]
Observations	14105	14105	6382	7723	6382	7723
R-squared	0.239	0.239	0.100	0.247	0.100	0.247
Occupation: Wage-employed						
Pseudo-tsunami x after pseudo-tsunami	-4.928	-4.739	-1.186	-5.841	-1.874	-4.709
	(3.337)	(3.914)	(1.072)	(5.485)	(1.090)	(6.598)
P-value - bootstrapped S.E.	0.162	0.277	0.231	0.350	0.120	0.522
Confidence Interval (95%)	[-17.037;5.418]	[-14.580;4.491]	[-7.867;1.595]	[-19.263;15.542]	[-5.429;0.448]	[-19.438;11.817]
Observations	14105	14105	6382	7723	6382	7723
R-squared	0.340	0.340	0.343	0.348	0.345	0.348
Occupation: Institutional investor						
Pseudo-tsunami x after pseudo-tsunami	-0.163	1.096	-1.375	1.713	-0.425	3.127
	(1.459)	(1.846)	(1.197)	(2.183)	(1.218)	(2.461)
P-value - bootstrapped S.E.	0.913	0.675	0.580	0.427	0.754	0.251
Confidence Interval (95%)	[-2.322;7.217]	[-2.214;8.356]	[-3.887;3.373]	[-1.743;10.761]	[-3.005;2.669]	[-1.577;12.080]
Observations	14105	14105	6382	7723	6382	7723
R-squared	0.375	0.375	0.219	0.374	0.219	0.374
Occupation: Not employed						
Pseudo-tsunami x after pseudo-tsunami	3.147**	2.929**	0.310	5.142*	0.396	4.277*
	(1.422)	(1.237)	(0.475)	(2.479)	(0.480)	(2.394)
P-value - bootstrapped S.E.	0.097	0.065	0.530	0.150	0.445	0.168
Confidence Interval (95%)	[-1.579;8.695]	[-0.247;5.828]	[-1.313;2.374]	[-4.552;13.716]	[-0.702;1.675]	[-2.547;9.663]
Observations	14105	14105	6382	7723	6382	7723
R-squared	0.182	0.182	0.167	0.188	0.167	0.188

Notes: See Table 6. Data from Rosca auctions in 14 branches from January 2003 to December 2004.

TABLE 10: Change in debt by occupational group, alternative definitions of near-coastal locations

			Run-up height		
Distance to coast	0-25km	0-15km	0-20km	0-50km	0-5 & 15-25km
Dependent variable: Debt (in 1,000 Rs.)	(1)	(2)	(3)	(4)	(5)
Occupation: Self-employed					
Tsunami x after tsunami	21.918***	21.062***	21.442***	20.324***	26.373***
	(3.141)	(3.409)	(3.050)	(2.994)	(3.827)
P-value - bootstrapped S.E.	0.001	0.009	0.001	0.005	0.012
Confidence Interval (95%)	[8.999;33.544]	[5.946;29.411]	[9.133;30.770]	[6.971;32.525]	[13.975;41.519]
Observations	12855	9678	10005	20413	8592
R-squared	0.539	0.585	0.560	0.498	0.571
Occupation: Wage-employed					
Tsunami x after tsunami	-11.156**	-9.414**	-9.950*	-7.604	-9.465**
	(4.572)	(4.191)	(4.938)	(6.214)	(3.340)
P-value - bootstrapped S.E.	0.082	0.090	0.099	0.237	0.098
Confidence Interval (95%)	[-27.136;5.280]	[-23.613;4.956]	[-28.438;5.889]	[-29.178;15.211]	[-29.022;15.856]
Observations	12855	9678	10005	20413	8592
R-squared	0.549	0.364	0.571	0.474	0.542
Occupation: Institutional investor					
Tsunami x after tsunami	-12.107**	-15.888***	-13.528**	-9.512**	-11.709*
	(4.356)	(3.869)	(4.720)	(4.431)	(5.492)
P-value - bootstrapped S.E.	0.387	0.290	0.326	0.429	0.371
Confidence Interval (95%)	[-18.614;13.142]	[-25.017;7.485]	[-21.645;12.949]	[-15.542;16.223]	[-51.736;64.546]
Observations	12855	9678	10005	20413	8592
R-squared	0.138	0.148	0.139	0.144	0.143
Occupation: Not employed					
Tsunami x after tsunami	1.219	1.490	1.542	1.451	1.198
	(5.692)	(6.219)	(6.134)	(5.387)	(6.347)
P-value - bootstrapped S.E.	0.752	0.730	0.727	0.766	0.730
Confidence Interval (95%)	[-6.323;21.242]	[-6.972;23.801]	[-6.767;23.164]	[-7.400;20.284]	[-7.778;28.632]
Observations	12855	9678	10005	20413	8592
R-squared	0.158	0.133	0.132	0.179	0.165
Number of clusters	14	11	12	25	8

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	Damage intensity				
Distance to coast	0-25km	0-15km	0-20km	0-50km	0-5 & 15-25km
Dependent variable: Debt (in 1,000 Rs.)	(6)	(7)	(8)	(9)	(10)
Occupation: Self-employed					
Tsunami x after tsunami	19.470***	19.238**	19.708***	17.141***	26.308**
	(4.852)	(6.322)	(5.566)	(4.147)	(7.605)
P-value - bootstrapped S.E.	0.001	0.019	0.006	0.002	0.012
Confidence Interval (95%)	[5.301;29.350]	[2.402;33.870]	[4.684;32.005]	[3.777;25.306]	[7.683;52.747]
Observations	12855	9678	10005	20413	8592
R-squared	0.539	0.585	0.560	0.498	0.571
Occupation: Wage-employed					
Tsunami x after tsunami	-11.232***	-10.043**	-10.648**	-6.921	-10.621***
	(3.669)	(4.018)	(4.665)	(5.824)	(1.810)
P-value - bootstrapped S.E.	0.026	0.049	0.057	0.257	0.004
Confidence Interval (95%)	[-20.119;-2.388]	[-19.051;-0.070]	[-22.493;0.587]	[-20.758;7.066]	[-18.401;-6.285]
Observations	12855	9678	10005	20413	8592
R-squared	0.549	0.364	0.571	0.474	0.542
Occupation: Institutional investor					
Tsunami x after tsunami	-6.772	-10.401	-7.824	-4.680	-5.245
	(5.925)	(6.091)	(6.601)	(5.584)	(7.338)
P-value - bootstrapped S.E.	0.462	0.312	0.425	0.572	0.598
Confidence Interval (95%)	[-19.069;9.270]	[-24.365;6.646]	[-21.360;10.540]	[-16.644;9.546]	[-27.088;38.723]
Observations	12855	9678	10005	20413	8592
R-squared	0.138	0.147	0.138	0.143	0.142
Occupation: Not employed					
Tsunami x after tsunami	1.365	1.912	1.920	1.491	1.565
	(4.259)	(4.636)	(4.556)	(4.089)	(4.729)
P-value - bootstrapped S.E.	0.761	0.710	0.717	0.760	0.723
Confidence Interval (95%)	[-6.098;14.428]	[-7.090;14.897]	[-6.786;14.964]	[-5.645;15.760]	[-10.477;20.902]
Observations	12855	9678	10005	20413	8592
R-squared	0.158	0.133	0.132	0.179	0.165
Number of clusters	14	11	12	25	8

Notes: See Table 6.

Appendix A Proofs

Proposition 1

Axioms 1 through 4 taken together imply that equation (2) can be written as the system of T non-linear equations

$$D_{iT,T} = 0,\ i = 1, ..., T \tag{1}$$

with the $T-1$ unknowns $r_1, ..., r_{T-1}$. The discount factor r_T does not appear in this system because $(1+r_T)$ is always raised to the power zero in (1). Denoting by $\mathbb{1}\{A\}$ the indicator function, which equals one if logical statement A is true and zero otherwise, this system of non-linear equations can be written as a system of T linear equations in matrix form, $Ax = b$, where x is of order $(T-1)\times 1$, b of order $T \times 1$ and A of order $T \times (T-1)$ with typical element $a_{ij} = \mathbb{1}\{i = j\}\widetilde{Pot}_i - \frac{1}{T}\widetilde{Pot}_j$, $x_j = (1+r_j)^{T-j}$, and b_i equals Pot/T for $i < T$ and $-\frac{T-1}{T}Pot$ for $i = T$, $i = 1, ..., T$, $j = 1, ..., T-1$. Noticing that x_j is strictly increasing in r_j for all $j = 1, ..., T-1$, a unique solution to $Ax = b$ will deliver the unique solution of (1).

We first prove the existence of a unique solution:

The rank of A is $T-1$. This can be shown by Gaussian elimination: consider the echelon form of A, A^*, which is obtained as follows: for row i of A^*, $i = 1, ..., T-1$, subtract A's row $i+1$ from A's row i. Row T of A^* is obtained by adding all T rows of A. Then $a^*_{ij} = \widetilde{Pot}_i$, $i = j$, $a^*_{ij} = -\widetilde{Pot}_j$, $j = i+1$ and $a^*_{ij} = 0$ otherwise. In words, A^* is a $T \times (T-1)$ upper triangular matrix augmented at the bottom by a $(T-1)$ row vector of zeros. This implies that A is of rank $T-1$, the number of unknowns, which implies that the linear system $Ax = b$ and hence (1) have a unique solution.

Further, straightforward substitution of $\frac{Pot}{\widetilde{Pot}_i}$ for x_i in $Ax = b$ confirms that $r_t = \left(\frac{Pot}{\widetilde{Pot}_t}\right)^{\frac{1}{T-t}} - 1$ is the unique solution to (1). ■

Proposition 2

For equation (3) notice from Proposition 1 that

$$\begin{aligned}
D_i &= \frac{1}{T}\sum_{t=1}^{T} D_{it,T} = \frac{1}{T}\sum_{t=1}^{T}\sum_{\tau=1}^{t}\left(\mathbb{1}\{\tau = i\} - \frac{1}{T}\right) Pot \\
&= \frac{Pot}{T}\sum_{\tau=1}^{T}\left[\left(\mathbb{1}\{\tau = i\} - \frac{1}{T}\right)\sum_{t=\tau}^{T} 1\right] \\
&= \frac{Pot}{T}\sum_{\tau=1}^{T}\left[\left(\mathbb{1}\{\tau = i\} - \frac{1}{T}\right)(T - \tau + 1)\right] \\
&= \frac{Pot}{T}\left[\frac{T+1}{2} - i\right] = \frac{Pot}{2}\frac{T+1-2i}{T}.
\end{aligned}$$

For equation (4), we depart from the third line of the proof just given, and notice that $\mathbb{1}\{t = i\} = x_{it}$,

$$D_i = \frac{Pot}{T}\sum_{t=1}^{T}\left[\left(x_{it} - \frac{1}{T}\right)(T - t)\right]. \tag{2}$$

The mean of x, $\frac{1}{T}\sum\limits_{t=1}^{T} x_{it}$, just equals $\frac{1}{T}$. Viewing the vectors $(x_{i1}, 1), ..., (x_{it}, t), ..., (x_{iT}, T)$ as a bivariate data sample, from the properties of empirical covariances it follows that, in (2), $(T - t)$ can be substituted by $-t$ and that instead of subtracting $\frac{1}{T}$ from x_{it}, we may add $\frac{1}{T}\sum\limits_{t=1}^{T} t = \frac{T+1}{2}$ to $-t$,

$$D_i = \frac{Pot}{T}\sum_{t=1}^{T}\left[-x_{it}\left(t - \frac{T+1}{2}\right)\right] = \frac{1}{T}\sum_{t=1}^{T} Pot\ T\ x_{it}\left(\frac{1}{2}\frac{T+1}{T} - \frac{t}{T}\right). \blacksquare$$

Corollary 1

The first formula follows from adding the left and right hand sides of equation (3) for all members of A. The second formula follows from adding the left and right hand sides of equation (4) for all members of A. $\blacksquare$

Appendix B Weights

Weights correcting for decile imbalances

To obtain consistent debt estimates for coastal and near-coastal branches before and after the tsunami, respectively, we define distinct decile weights for each of four groups of observations. These groups are defined by the two indicators $after$ and $coastal$, where $after$ is defined as in (1) and $coastal$ takes a value of one for all observations from coastal branches and zero otherwise. For an observation indexed by b, d, g and t, the weight is

$$f_{bdgt} = \frac{1}{10} \frac{N_{after_{bdgt},coastal_b}}{n_{after_{bdgt},coastal_b,dec_{dt}}},$$

where dec_{dt} denotes the Rosca decile in which auction $bdgt$ takes place, $n_{after,coastal,dec}$ the number of observations in decile dec in which the auction takes place given the values of $after$ and $coastal$; $N_{after,coastal}$ is the total number of observations given the values of $after$ and $coastal$, which equals $\sum_{dec} n_{after,coastal,dec}$. For each combination of $after$ and $coastal$, this weight is simply the inverse of the relative frequency of observations in decile dec, relative to all observations for the same combination of $after$ and $coastal$.

Weights correcting for missing occupation information

As the weight we calculate the ratio of the true probability that occupation k occurs and the probability that it occurs in our data under assumptions (i) and (ii). We do this separately for each combination of $after$ and $coastal$. The weight for occupation k then is

$$p^k_{bdgt} = \begin{cases} \frac{n_{after_{bdgt},coastal_b,dec_{dt}} - n^I_{after_{bdgt},coastal_b,dec_{dt}}}{n_{after_{bdgt},coastal_b,dec_{dt}} - n^I_{after_{bdgt},coastal_b,dec_{dt}} - n^M_{after_{bdgt},coastal_b,dec_{dt}}}, k = \text{self, wage, not-emp.} \\ 1, \; k = inst\ inv\ (I) \\ 0, \; k = \text{ missing occupation } (M), \end{cases}$$

where k indexes occupations, $n^k_{.,.,dec}$ is the number of observations in decile dec with occupation k conditional on values of $after$ and $coastal$, M denotes the missing occupation category, and I the institutional investor.

Appendix C Supplementary material

Table C.1: Rosca denominations

Duration (in months) (1)	Monthly contribution (in Rs.) (2)	Pot (in Rs.) (3)	Frequency All branches (4)	Near-coastal branches (5)	Coastal branches (6)
25	400	10,000	857	474	383
25	600	15,000	31	0	31
25	1,000	25,000	636	285	351
25	2,000	50,000	647	303	344
25	4,000	100,000	241	58	183
25	20,000	500,000	7	0	7
30	500	15,000	1,189	637	552
30	1,000	30,000	296	205	91
30	1,500	45,000	19	0	19
30	2,000	60,000	65	57	8
30	2,500	75,000	6	6	0
30	5,000	150,000	247	175	72
30	10,000	300,000	105	70	35
30	20,000	600,000	12	12	0
30	30,000	900,000	13	0	13
40	250	10,000	4,020	2,374	1,646
40	375	15,000	232	178	54
40	500	20,000	155	60	95
40	625	25,000	1,739	961	778
40	750	30,000	152	109	43
40	1,250	50,000	1,770	1,151	619
40	1,500	60,000	38	16	22
40	2,500	100,000	2,260	1,212	1,048
40	5,000	200,000	293	200	93
40	7,500	300,000	110	66	44
40	12,500	500,000	187	60	127
40	15,000	600,000	77	41	36
40	25,000	1,000,000	32	17	15
50	200	10,000	20	20	0
50	400	20,000	22	22	0
50	500	25,000	62	19	43
50	1,000	50,000	609	240	369
50	2,000	100,000	110	0	110
50	6,000	300,000	42	20	22
50	10,000	500,000	71	29	42
50	20,000	1,000,000	12	0	12
60	1,250	75,000	22	0	22
60	5,000	300,000	13	0	13

Notes: A Rosca denomination is a distinct combination of duration in months, which is equal to the number of participants, and the monthly contribution.

Table C.2: Descriptive statistics: Financial data in the placebo experiment (2003 and 2004)

	All auctions			Auctions before tsunami		
	All branches	Min	Max	Near-coastal branches	Coastal branches	p-value F-test
	(1)	(2)	(3)	(4)	(5)	(6)
Duration (in months)	35.54	25	60	35.39	34.92	0.526
	(7.18)			(6.80)	(7.83)	
Monthly contribution (in Rs.)	1,569	200	30,000	1,501	1,725	0.124
	(2,729)			(2,556)	(3,144)	
Pot (in Rs.)	55,839	10,000	1,000,000	52,703	60,487	0.114
	(100,075)			(91,633)	(113,344)	
Turnover (in 1,000 Rs.)	2,067	250	5,000	1,911	2,229	0.089
	(3,904)			(3,434)	(4,401)	
Winning bid (in Rs.)	14,432	500	400,000	15,833	18,212	0.150
	(30,102)			(30,961)	(39,424)	
Relative winning bid (in %)	22.717	5	40	26.525	26.074	0.473
	(12.020)			(11.565)	(11.668)	
Round of auction	13.608	1	37	9.871	9.725	0.638
	(7.834)			(5.736)	(5.615)	
Relative round of auction	0.397	0	1	0.294	0.294	0.988
	(0.238)			(0.192)	(0.188)	
Income recorded by lender*	0.861	0	1	0.918	0.890	0.634
	(0.346)			(0.275)	(0.313)	
Occupation recorded by lender	0.720	0	1	0.804	0.719	0.054
	(0.449)			(0.397)	(0.450)	
Cosigner (incidence)*	0.683	0	1	0.779	0.739	0.507
	(0.465)			(0.415)	(0.439)	
Number of cosigners*	1.558	0	10	1.945	1.748	0.182
	(1.336)			(1.323)	(1.336)	
Arrear (incidence)*	0.627	0	1	0.724	0.728	0.917
	(0.484)			(0.447)	(0.445)	
Arrear amount (relative to pot)*	0.067	0.000	0.894	0.086	0.104	0.236
	(0.110)			(0.123)	(0.143)	
Legal enforcement*	0.228	0	1	0.276	0.408	0.115
	(0.420)			(0.447)	(0.492)	
Occupation of auction winners						
Self-employed	0.083	0	1	0.104	0.076	0.312
	(0.276)			(0.305)	(0.265)	
Wage-employed	0.202	0	1	0.230	0.227	0.876
	(0.401)			(0.421)	(0.419)	
Institutional investor	0.387	0	1	0.420	0.369	0.216
	(0.487)			(0.494)	(0.483)	
Not-employed	0.048	0	1	0.050	0.048	0.936
	(0.214)			(0.217)	(0.213)	
Occupation not recorded by lender	0.280	0	1	0.196	0.281	0.052
	(0.449)			(0.397)	(0.450)	
Number of observations	19,678			4,451	3,746	

Notes: See Table 2. Data from Rosca auctions in 14 branches from January 2003 to December 2004.
*Only observations from recipients of pots other than the institutional investor (12,095 auctions).