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Financial market responses to a natural disaster: Evidence from credit networks and the Indian Ocean tsunami

Kristina Czura [a,*], Stefan Klonner [b]

[a] University of Groningen, The Netherlands
[b] Heidelberg University, Germany

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ABSTRACT

We examine 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 we estimate the causal effect of this major natural disaster on financial flows between occupational groups, the price of credit and other loan characteristics. We find that the supply of funds in these credit networks remained remarkably stable, while demand by small and medium-scale entrepreneurs increased significantly. In response, substantial funds were channeled from wage-employed members and commercial investors to entrepreneurs. We conclude that natural disasters affect individuals with substantial heterogeneity and that the Roscas we study offer more scope for gains from trade in response to a seemingly aggregate shock than commonly assumed for traditional credit and insurance networks.

1. Introduction

Natural disasters, most often in the form of drought or flood, are among the most severe shocks jeopardizing the livelihoods of the poor around the developing world (World Bank, 2014, p. 55). Since markets for insurance are largely missing, households engage in various market and non-market transactions to deal with risks, and credit plays an important role as an insurance substitute (Eswaran and Kotwal, 1989; Besley, 1995a and Besley, 1995b). In particular idiosyncratic shocks, such as health shocks or individual crop losses, appear to be well insured (Townsend, 1994; Udry, 1994), but little is known on how households cope with damages caused by natural disasters and what role credit and insurance networks play in this process. While access to formal finance alleviates economic consequences of a natural disaster, the supply of funds tends to be severely restricted in its aftermath (Becchetti and Castriota, 2011; Berg and Schrader, 2012; Gallagher and Hartley, 2017). Most authors express a general skepticism regarding the potential of local networks for mitigating the effects of such shocks (Morduch, 1999; Fafchamps et al., 1998; McKenzie, 2003; De Mel et al., 2012).

Despite the locally concentrated damage, natural hazards affect households with considerable heterogeneity, even within villages or neighborhoods (Townsend, 1994, 1995; Kurosaki, 2017; Gallagher and Hartley, 2017). For flood damages, De Mel et al. (2012) and Deryugina et al. (2018) have found that small and medium-scale entrepreneurs were far more severely affected than other households in the aftermath of the 2004 Indian Ocean tsunami and Hurricane Katrina. We view these heterogeneous effects as idiosyncratic components of a seemingly aggregate shock, which generate scope for gains from trade in risk sharing and credit networks.[1] We think that this potential for mutual insurance, even within a given location, has been largely overlooked so far.

In this paper we provide causal evidence on such insurance in credit networks in the aftermath of a natural disaster. We empirically study the effect of one of the most devastating disasters in the last decades – the 2004 Indian Ocean tsunami – on Rotating Savings and Credit Associations (Roscas), 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 Rosca 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.

* Corresponding author.
E-mail addresses: k.czura@rug.nl (K. Czura), klonner@uni-heidelberg.de (S. Klonner).

[1] We refer to such a shock as ‘seemingly aggregate’ because it is not a pure aggregate shock but a shock that seems aggregate in nature while containing large idiosyncratic components at the same time.

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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. We find a significant increase in the competition for loans on the demand side in response to the tsunami, which is manifested in a nine-percent increase in the price of credit in coastal locations. Lastly, we find that sizable funds are channeled to small and medium-scale entrepreneurs, a group that has previously been shown to be particularly affected by this natural disaster and exhibits especially high returns to replacement investments (De Mel et al., 2012). Their net 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 US Dollar ($) 526 (not purchasing-power adjusted) per self-employed Rosca member and $ 1.4 million 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. This result suggests that the credit networks studied here channel capital to the presumably most productive investments in a quick and flexible fashion.

Our financial data is particularly suited for this endeavor. They come from bidding Roscas, which are group-based mutual financing schemes that combine inflexible contributions with flexible loans. They have several attractive features: First, there is scope for gains from trade arising from the flexibility of the credit allocation mechanism. 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 Roscas that we study 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. Finally, the Roscas that we study are an eminent example of a middle-rung financial institution which combines both elements of formal and informal finance, and form an important part of the financial architecture in low- and middle-income countries (Besley, 1995b).[3]

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 economic shocks that seem predominantly aggregate in nature. 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 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, 1994; Fafchamps and Gubert, 2007). For example, Fafchamps and Lund (2003) show that informal financial transactions within risk-sharing networks respond to idiosyncratic shocks in the Philippines. On the other hand, research on credit as insurance mechanism in the face of natural disasters is scarce, despite the fact that these hazards severely jeopardize the livelihoods of the poor.[4] The small body of research on the role of credit for coping with such shocks is exclusively concerned with access to formal credit and microcredit, its effect 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; Shoji, 2010). These observational studies face considerable challenges regarding the empirical identification of the causal effect of access to finance.[5] 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 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, we focus on a popular indigenous financial institution that combines elements from both informal credit markets and formal finance (see Munshi (2005)). This form of an intermediate, middle-rung financial institution reaches out to many more households in our study context than banks (Kapoor et al., 2011), but its potential to provide mutual insurance has been largely overlooked by this literature. Second, while most of the literature differentiates between aggregate and idiosyncratic shocks and focuses mostly on the latter, we explore idiosyncratic components of a seemingly aggregate shock, a natural disaster. And third, we show that financial intermediation in these Roscas responds quickly and channels funds to a group that is especially severely affected by the tsunami, small to medium-scale entrepreneurs. This central finding complements the results of 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, 2003, 2008). These papers stress the importance of the concurrent auction credit allocation mechanism of bidding Roscas for their insurance role. The focus in this literature is exclusively on idiosyncratic income or expenditure shocks. Our contribution is that we show empirically how bidding Roscas also provide insurance in the aftermath of a seemingly aggregate shock by intermediating between different occupational groups. Secondly, we contribute to a theoretical literature on Roscas that addresses their optimality as a

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

[3] For India, Eeckhout and Munshi (2010) state that deposits in registered Roscas amounted to 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.

[4] 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.

[5] Better empirical identification has been achieved in earlier work that documents how labor markets help to mitigate the effects of aggregate agricultural shocks (Walker and Ryan, 1990; Rose, 2001) and in recent work that considers migration as a coping strategy for dealing with environmental hazards (Yang and Martínez, 2007; Gröger and Zylberberg, 2016).

savings institution (Besley et al., 1993, 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, financial markets and economic growth. On a broader note, short-term and long-term impacts of natural disasters on overall economic development seem limited (Cavallo et al., 2013). Our study identifies an important mechanism through which the harmful economic effects of such disasters are mitigated, the re-allocation of funds to entrepreneurs in credit networks. With regard to natural disasters and financial markets, the common finding in this literature is that, while access to formal finance helps to mitigate the economic consequences of a natural disaster, the supply of funds tends to be severely restricted during its aftermath.[6] 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 and therefore cannot influence prices. Further, for the important financial institution that we study, we do not observe a market contraction 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 a 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.

2. Background and data

2.1. 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; Government of Tamil Nadu, 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).[7]

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.[8] Their study on enterprise recovery documents that access to capital is of utmost importance for microenterprises' recovery in the aftermath of such a natural disaster given the extraordinarily high returns to the necessary replacement investments. In particular, retailers benefited disproportionately from replenishing inventories.

The immense destruction of the tsunami triggered sizable relief and reconstruction efforts. The three largest rehabilitation schemes were the Asian Development Bank's Tsunami Emergency Assistance Project (TEAP) of $ 200 million, the Government of India's Rajiv Gandhi Rehabilitation Package (RGRP) of more than $ 800 million, and the Emergency Tsunami Reconstruction Project (ETRP) of $ 465 million, which was partially funded by the World Bank (Government of Tamil Nadu, 2005b). While these relief packages were implemented to reconstruct infrastructure and to provide housing and replacement of boats and fishing equipment for affected households, 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. The Emergency Tsunami Reconstruction Project (ETRP) was committed in May 2005 and the first disbursement of $ 50 million took place in October 2005. As we show below, there is only limited overlap of the government's reconstruction funding and the time period covered by our financial data, where 55 percent of post-tsunami loans are awarded between January and April 2005.

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), see Fig. 1.[9]

[6] Berg and Schrader (2012) study microfinance loans after volcanic eruptions in Ecuador; Romero 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.

[7] 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; Government of Tamil Nadu, 2005b).

[8] 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).

[9] Other common definitions of tsunami intensity are Soloviev's (1970) $i=\log_2(\sqrt{2}*$ run-up height), which is also used by the United States' National Geophysical Data Center, and Shuto's (1993) $i=\log_2$(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.

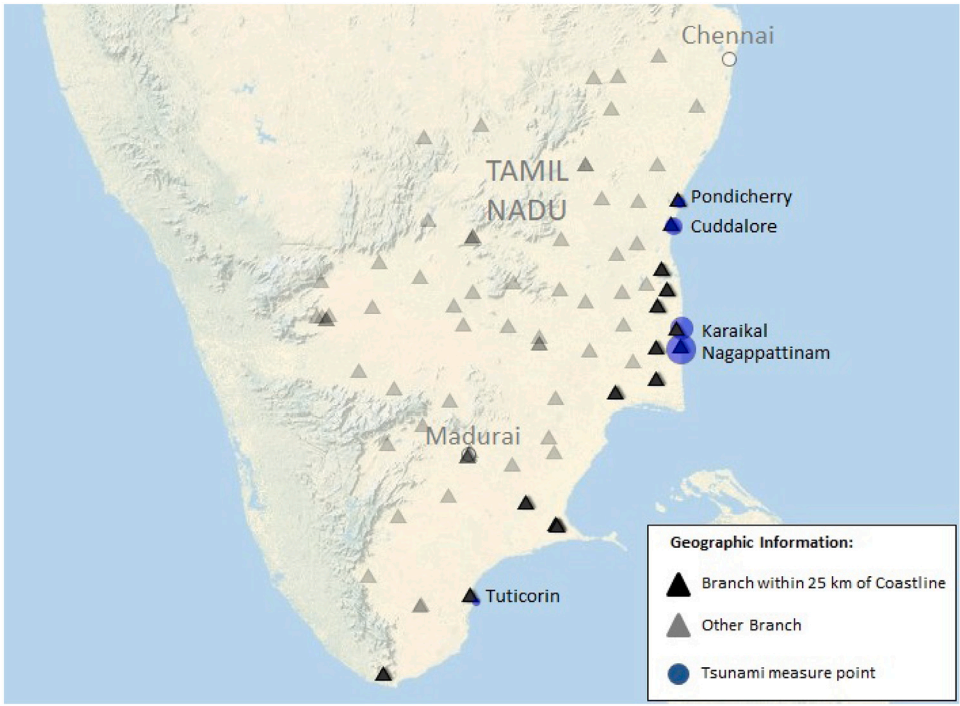

Fig. 1. Tsunami intensity and branch locations.
Notes: The map depicts all branches of the organizer in Tamil Nadu (except for the state capital Chennai) as triangles. Larger cities may have multiple branches. Black triangles with town names represent coastal branches within our research design, black triangles without branch town names near-coastal branches. The size of the circle for the tsunami measure points is scaled by the run-up height at this location. The corresponding damage intensities are VII (damaging) in Pondicherry, IX (destructive) in Cuddalore, IX+ (destructive to very destructive) in Karaikal, X (very destructive) in Nagappattinam, and VI+ (slightly damaging to damaging) in Tuticorin.

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 exclude all branches which are more than 25 kilometers away from the coastline to ensure that all sample branches are embedded in a homogeneous economic environment prior to the tsunami. All remaining 14 branches are located in medium-sized metropolitan areas or towns. We inspected the administrative borders of these metropolitan areas and towns using Google Maps and found that the coastline forms part of these borders for five of them. In what follows, we will refer to the latter as 'coastal' and the other nine locations as 'near-coastal'. Incidentally, the branches in the five coastal locations are all closer than five kilometers to the coastline, while the remaining nine branches are seven and more kilometers away. Given an inundation distance of no more than three kilometers along the coastline of Tamil Nadu (Narayan et al., 2005), we assign the tsunami wave's run-up height and the observed damage intensity at the nearest survey location given in Maheshwari et al. (2005) and Narayan et al. (2005) to the coastal branches and a run-up height and damage intensity of zero to the near-coastal branches.

For the five coastal branches 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 10 (*very destructive*) in Nagappattinam, which was the most affected city on the Indian coast with 6,065 casualties, 76 percent of all deaths in Tamil Nadu (Government of Tamil Nadu, 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 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. 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, which are flexible with regards to the timing of borrowing and the interest rate (Besley et al., 1993).

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 afterward. 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.[10] 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 defined as the amount of funds auctioned is completely inelastic.

The data we use come from one single commercial organizer of bidding Roscas operating 78 branches in the state of Tamil Nadu in 2004 and 2005 (see Eeckhout and Munshi (2010) for a detailed description of the Rosca organizer). 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. The Rosca organizer reports his activities to a regulatory authority, Tamil Nadu's Chit Fund Registrar, but overall faces far less supervision and regulatory intervention than banks (Kapoor et al., 2011). The resulting financial networks provide access to credit for individuals who often do not have access to bank credit. Roscas incorporate several features of traditional informal finance. First, instead of physical collateral, the organizer mainly relies on social collateral to ensure continued contributions to the scheme by members who have received a pot. In particular, guarantors, or cosigners, are requested who pledge to step in for any missed future contribution owed by the borrower. Second, upon winning an auction, members may be screened, which involves the recording of the prospective borrower's occupation, income, and employer or type of business. Third, borrowers who are in arrear are pressured not only through letters and phone calls but also through visits to their homes.[11] Fourth, there is an individual dynamic incentive. The company keeps black lists of defaulters, who are denied participation in future Roscas. 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.

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 groups in the sample are homogeneous 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 1
Descriptive statistics: Geophysical data.

	Mean (1)	Standard deviation (2)	Minimum (3)	Maximum (4)
Auctions in all branches (19,594 observations)				
Run-up height (in meters)	2.591	3.430	0	11
Damage intensity	3.578	4.063	0	10
Auctions in near-coastal branches (10,786 observations)				
Run-up height (in meters)	0	0	0	0
Damage intensity	0	0	0	0
Auctions in 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.

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. 11,329 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 higher 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 recipient'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,

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

[11] 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.

[12] The Tamil Nadu government imposes a bid ceiling on winning bids relative to 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./\$ and will be used for all currency conversions. The average pot hence equals around \$ 1,300.

[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).

Fig. 2. Occupational composition of borrowers at baseline (in 2004), by Rosca duration decile.
Notes: Occupational composition of borrowers (y-axis) for each Rosca duration decile (x-axis) at baseline in 2004 before the tsunami.

students and pensioners).[17] Finally, 51.6 percent of these pots (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 is low. This ensures an attractive rate of return for other, non-corporate members who value Roscas primarily as a financial investment. At the same time the institutional investor has a gain from making arbitrage profits across groups and branches.[18] By doing so, he reduces fragmentation in this 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.

Important for our later econometric analysis, the occupational composition of winners of pots varies systematically over the course of a Rosca. Fig. 2 illustrates this for Rosca auctions in 2004, prior to the tsunami by depicting the occupational composition of auction winners. 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.[19] During the first seven deciles, 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.[20] 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. We will build on this framework to quantify the extent of financial intermediation between different occupational groups of Rosca participants and derive estimating equations for the auction-level data that we have collected.

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.

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

[18] Klonner and Rai (2010) show in data from before the tsunami that the institutional investor arbitrages across branches by borrowing in groups with low implicit interest rates and saving in groups with high ones.

[19] 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 institutional investor obtains 42.5 percent of pots in the first decile in Fig. 2.

[20] 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.

Table 2
Descriptive statistics: Financial data.

	All auctions			Auctions before tsunami		
	All branches (1)	Min (2)	Max (3)	Near-coastal branches (4)	Coastal branches (5)	p-value F-test (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[a]	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)[a]	0.543	0	1	0.665	0.593	0.177
	(0.498)			(0.472)	(0.491)	
Number of cosigners[a]	1.106	0	9	1.450	1.256	0.081
	(1.250)			(1.306)	(1.287)	
Arrear (incidence)[a]	0.444	0	1	0.579	0.536	0.226
	(0.497)			(0.494)	(0.499)	
Arrear amount (relative to pot)[a]	0.033	0	1	0.048	0.048	0.971
	(0.068)			(0.082)	(0.085)	
Legal enforcement[a]	0.086	0	1	0.108	0.197	0.186
	(0.280)			(0.311)	(0.398)	
Occupation (incidence) 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 and standard deviations in parentheses for all auctions in columns 1 to 3 and for auctions before the tsunami on December 26, 2004 in columns 4 and 5. 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.

[a]Only observations from recipients of pots other than the institutional investor (12,960 auctions).

In our data set, an observation is a Rosca auction. Each observation is uniquely identified by its branch (indexed by b), Rosca denomination (indexed by d), group (indexed by g) and round (indexed by t) identifiers.[21] Our basic estimating equation is

$$y_{bdgt} = \alpha + \gamma \; after_{bdgt} + \delta \; tsunami_b + \beta \; tsunami_b \times after_{bdgt} + u_{bdgt}, \quad (1)$$

where the dependent variable y_{bdgt} is a financial outcome in round t in Rosca group g of denomination d in branch b. The variable $tsunami_b$ is a measure of local tsunami intensity, either the *run-up height* of the tsunami wave or the *damage intensity* in location b. We use the tsunami intensity at the branch level as our financial data does not reliably identify the geolocation (or address) of Rosca participants. The dummy variable $after_{bdgt}$ indicates whether an auction took place after the tsunami; it equals zero for all auctions before December 26, 2004 and one for all auctions after this date.

To account for unobserved heterogeneity, we augment this basic equation by a number of fixed effects and eventually use the estimating equation

$$y_{bdgt} = \rho_{bd} + \sum_{m=1}^{22} \gamma_m Month^m_{bdgt} + \beta \; tsunami_b \times after_{bdgt} + u_{bdgt}, \quad (2)$$

where the term ρ_{bd} is a cross-sectional fixed effect accounting for unobserved branch- and denomination-specific heterogeneity, which absorbs the regressor parametrized by the coefficient δ in Eq. (1). We define $Month^m_{bdgt}$ as a dummy equal to one if auction $bdgt$ occurs in month m ($m = 1, \ldots, 22$, where 1 corresponds to January 2004). Effectively, γ_m is a time fixed effect for month m, which absorbs the before/after indicator $after_{bdgt}$ in Eq. (1). In sum, our difference-in-differences strategy is implemented through the cross-sectional fixed effects ρ_{bd}, the time fixed effects γ_m, and the interaction term of interest $tsunami_b \times after_{bdgt}$.

Our choice of estimating equation is driven by the following factors. First, due to limited degrees of freedom, we cannot include Rosca

[21] 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.

group fixed effects (ρ_{bdg}), which would amount to identifying the effects of interest only within group. There are 1,069 Rosca groups in our data and 12,855 observations in our key estimations, where we identify participation of four different occupational groups. Instead, our empirical identification involves comparisons both within Rosca group and across Rosca groups of the same denomination. Within Rosca denomination, our estimations implicitly average effects over groups that are affected at different times of their cycle, e.g. in the third and in the tenth month. Accounting for heterogeneous exposure to the tsunami not only in terms of wave height or damage intensity but also timing within the Rosca cycle would require further structural assumptions, which we aim to avoid here.

Second, the data does not allow us to aggregate the auction-level observations to the Rosca group and conduct the analyses at this level because close to 70 percent of auctions in our estimation sample are from Rosca groups which were still ongoing at the time of data collection in late 2005. This is owed to the fact that Roscas in our sample span up to five years with a mean duration of three (see Table 2). Instead, we will derive regression specifications at the auction level to measure credit flows and debt by occupational group directly from an accounting framework developed in the next section.

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 challenge of this clustering rule is that there are just 14 clusters and conventional cluster-robust standard errors are likely 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).

3.2. Financial intermediation in Roscas

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 $-z + \frac{p_t}{T} = -\frac{1}{T}(Pot - p_t)$ 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 decreases her debt), while the winner of that pot increases his borrowings (or decreases his savings). A conceptual challenge, which is thus far unresolved to the best of our knowledge, 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, we will construct a measure of average debt for each Rosca participant which aggregates her average 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 in Rosca round t is the sum of the present values of her net payoffs accruing in rounds 1 through t.*

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

Axiom 3. *Time variation in the discount factor: For each t, there is a distinct discount factor for payoffs in that period, r_t.*

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

To provide some intuition for these axioms, suppose that, in each time period, all Rosca participants face a given interest rate for borrowings and savings they make in this period. And this interest rate is locked in in the sense that it applies to all savings and borrowings made in t until the termination of the scheme. Then, given a vector of interest rates which makes all four axioms hold, the net financial balance of each participant will equal Rosca debt as just axiomatized in each period.

Proposition 1. *Axioms 1 through 4 imply that*

$$D_{it,t'} = \sum_{\tau=1}^{t}(1+r_\tau)^{t'-\tau}\left(x_{i\tau} - \frac{1}{T}\right)\widetilde{Pot}_\tau, \tag{3}$$

where $r_t = \left(\frac{Pot}{\widetilde{Pot}_t}\right)^{\frac{1}{T-t}} - 1,\ t = 1, \ldots, T-1,$

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 $\hat{p}_t/(T-t)$, where $\hat{p}_t$ is the winning bid in period t relative to the full pot, zT. Hence winning bids reflect an 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 ratre is straightforward, 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 these axioms, debt is always well-defined. This would in general fail to be the case for winners of intermediate pots if Axiom 3 were replaced, for example, by the requirement that the implicit interest rate varies over participants while being 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. *Average debt of the Rosca participant who obtains the pot in round t evaluated at the termination of the Rosca, is*

$$D_t = \frac{1}{T}\sum_{\tau=1}^{T} D_{i\tau,T} = \frac{Pot}{2}\frac{T+1-2t}{T}, \tag{4}$$

which can equivalently be written as

$$D_t = \frac{1}{T}\sum_{\tau=1}^{T} T\ Pot\ x_{t\tau}\left(\frac{1}{2}\frac{T+1}{T}-\frac{\tau}{T}\right), \tag{5}$$

where $x_{t\tau} = \begin{cases} 1 & \text{if } t=\tau \\ 0 & \text{otherwise.}\end{cases}$

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 Eq. (4) 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 ($t = 1$), 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 ($t = T$) 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 given further above with three members and a monthly contribution of \$10 per member, implying a pot of \$30 and a net value of the pot of \$20.*

Month	1	2	3
$D_{it,T}$ (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.

Eq. (5) 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 two time-varying ones, t and x, and two time-invariant ones, the pot amount and the 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 account 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*

$$D^A = s_A\frac{Pot}{2}(T+1-2\bar{t}^A), \tag{6}$$

which can equivalently be written as

$$D^A = \frac{1}{T}\sum_{t=1}^{T} Pot\ T\ x_t^A\left(\frac{1}{2}\frac{T+1}{T}-\frac{t}{T}\right). \tag{7}$$

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 Eq. (6) is

$$D^A_{\max} = s_A(1-s_A)\frac{T\ Pot}{2}, \tag{8}$$

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 debt of different professional groups by regression methods. The unit of observation is a single Rosca round (or auction), as laid out in Eq. (2). 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, Eq. (7), 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*.

We end this subsection with a caveat. The formalism just developed is a novel accounting framework for capturing debt in a Rosca in a consistent and transparent way, even when winning bids bounce around from round to round and internal rates of return for the payoff flows of individual participants have only imaginary solutions. It is *not* a structural model of credit demand and the resulting (endogenous) winning bids in a Rosca. Rather conversely, it takes winning bids, which may well arise from time- and individual-specific transitory or permanent shocks to credit demand, as given and delivers a measure of average debt for each participant by endogenously fitting a vector of discount rates which are uniform across participants — for the sake of treating each participant equally as far as accounting is concerned. In the sequel, we approach the effects of the tsunami on financial allocations in Roscas in a reduced-form fashion and do not attempt to formulate a structural model of credit demand and bidding in Roscas, for which our accounting framework would be completely inapt. We think that our approach generates more value in the present research context as it delivers easily interpretable effect magnitudes in currency units rather than just effect directions on structural parameters that are merely constructs and heavily dependent on modeling assumptions.

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. Our analysis builds on two stylized facts established in previous work: First, self-employed are more affected than other households by a natural disaster and hence have higher credit demand because they lose business *and* household assets and thus have higher returns to (replacement) investments (see De Mel et al., 2012 and Deryugina et al., 2018). Hence we expect a greater increase in credit demand among self-employed than other Rosca participants. Second, it holds across all models of bidding Roscas that we are aware of (Besley et al., 1993; Kovsted and Lyk-Jensen, 1999; Klonner, 2003, 2008; Eeckhout and Munshi, 2010), that higher credit demand by a Rosca member translates into an earlier rank of that member in a bidding equilibrium. Finally, our theoretical framework allows to relate changes in ranks to changes in debt.

Most of our empirical analysis is guided by the formulas for debt spelled out in Eqs. (6) and (7). 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.[22] This concept of Rosca deciles, moreover, allows us to pool data from different Rosca denominations. Our difference-in-differences estimating equation for the probability of group A winning a pot in decile τ is

$$x^A_{bdgt} = \sum_{\tau=1}^{10}\left[1\left\{\frac{\tau-1}{10} < \frac{t}{T_d} \le \frac{\tau}{10}\right\}\left(\begin{array}{c}\alpha_\tau tsunami_b + \delta_\tau after_{bdgt}\\ +\beta_\tau tsunami_b \times after_{bdgt}\end{array}\right)\right] \quad (9)$$
$$+\rho_{bd} + \sum_{m=1}^{22}\gamma_m Month^m_{bdgt} + u_{bdgt},$$

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 Eq. (2) to a situation of heterogeneous treatment effects by Rosca decile.

Second, we will examine D^A as given in Eq. (7). We draw on estimating Eq. (2) to accommodate Roscas of different denominations and estimate the effect of the tsunami on the average debt of occupational group A by

$$x^A_{bdgt}\left(\frac{1}{2} - relround_{bdgt}\right)T_d Pot_d = \rho_{bd} + \sum_{m=1}^{22}\gamma_m Month^m_{bdgt} + \beta\ tsunami_b \times after_{bdgt} + u_{bdgt}, \quad (10)$$

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 Eq. (2).

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 toward 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 Eq. (10). To see this, consider a simple regression of $x_t^A(1/2 - t/T)$ 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. 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 toward the end, when the organizer faces less financial exposure (see Fig. 2). To see how this jeopardizes consistent estimation of D^A as given in Eq. (6), consider again a simple regression of $x_t^A(1/2 - t/T)$ 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 Eq. (6) 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 Eq. (2). 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).

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 toward 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 Eqs. (9) and (10).

4. Results

4.1. Attrition, supply and market size

Although supply of funds 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

[22] 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.

Table 3
Recording of occupations by the Rosca organizer.

Dependent variable:	Missing occupation (dummy)	
Tsunami intensity measure:	Run-up height (1)	Damage intensity (2)
Tsunami × 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 not recorded, i.e. missing. Weighted OLS: f-weights correcting for imbalances over Rosca deciles included, see Section 3.3 for details. Data from Rosca auctions in 14 branches from January 2004 to October 2005. Mean of dependent variables reported for the full sample. 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.

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 and retrieve her contributions 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 Eq. (2) 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 column 1 of Table 4, there is no change in the relative frequency of memberships held by the institutional investor in response to the tsunami.[23]

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 measured both at the auction level and aggregated within a branch in the respective month, and the number of new Roscas started per branch per month.[24] We do not observe any change in the incidence of new Roscas started at the auction level (Table 4, column 2) and the branch level (Table 4, column 3), or in the number of new Roscas started (Table 4, column 4) in response to the tsunami.

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, columns 5 to 7, the point estimates are very small in magnitude 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.[25]

4.2. Flow of funds between occupational groups

The central econometric result of our analysis is foreshadowed by the occupational profiles set out in Fig. 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 in near-coastal branches before and after the tsunami.

We explore this pattern more formally by conducting regression analyses based on estimating Eq. (9). Because of the multitude of estimated coefficients we present these results graphically in Fig. 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 Fig. 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 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).[26] 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 heterogeneous economic effect of the tsunami on different occupational groups, in particular on self-employed members.

We proceed to analyze how this shift in the different occupational groups' ranks translates into changes in debt according to Eq. (10). According to the results set out in column 2 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 $ 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 5).

Conversely, the 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, Table 6,

[23] This also implies that there are no changes in the funds supplied by the institutional investor.

[24] For these three measures we use all 19,955 auction observations available to us and also consider Roscas that started after the tsunami which are excluded in our main sample due to selection concerns. 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.

[25] 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).

[26] To verify that the share of self-employed participants did not change in response to the tsunami, we conduct the following test: First, we deal with increased screening by randomly recoding a fraction of the occupations after the tsunami as missing — branch-wise according to the point estimates set out in Table 3, panel A. We then use the incidence of each individual occupation in this synthetic data set as dependent variable in Eq. (9). We do not find any change in the incidence of self-employed or any other occupation winning an auction. Additionally, when we compare the historical share of each occupational category in all terminated Rosca groups (for which we can determine the exact distribution of occupations), we do not find any difference to the shares in our sample (Table 5, first panel). Thus, we are confident that there is no relevant change in the occupational composition of Rosca participants in response to the tsunami.

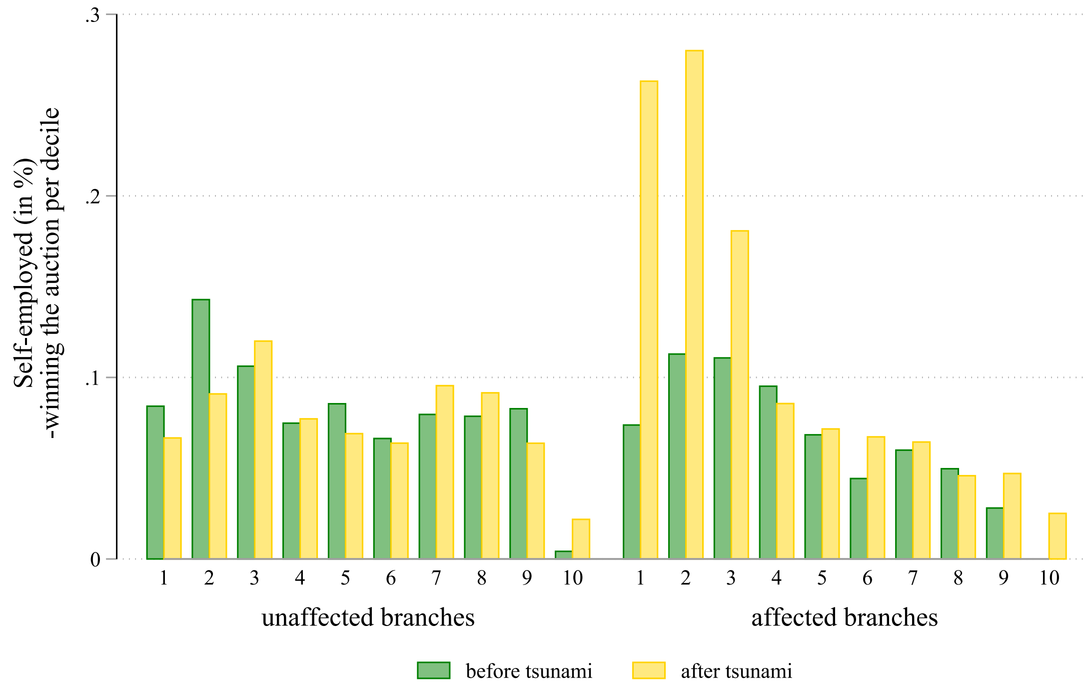

Fig. 3. Relative frequency of self-employed Rosca participants.
Notes: Percentage share of self-employed winning an auction (y-axis) per Rosca decile (x-axis) for near-coastal and coastal branches, before and after the tsunami.

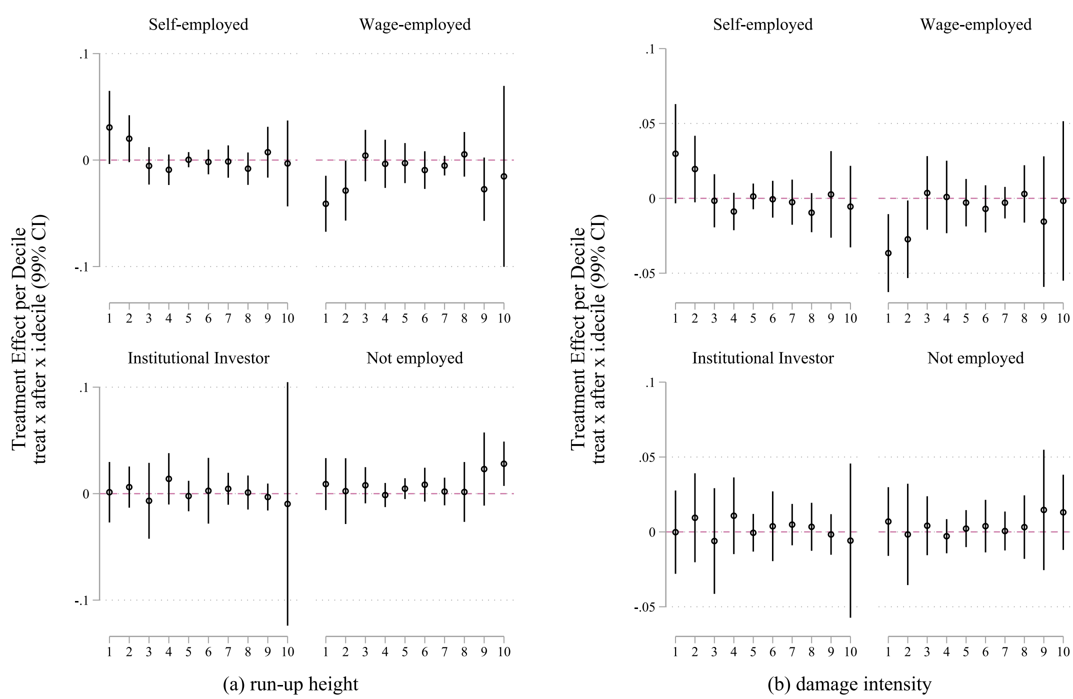

Fig. 4. Changes in the relative frequency of occupations caused by the tsunami, by Rosca decile.
Notes: Plots depict the estimated β-coefficients of estimating Eq. (9) for the different occupational groups. Dependent variable: Dummy for occupational group A if auction is won by group A, where A equals '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 correcting for imbalances over Rosca deciles and missing occupations included in all estimations, see Section 3.3 for details.

Table 4
Market characteristics: Attrition in Roscas and market size.

	Attrition	Supply			Market size		
	Institutional investor (incidence)	New Rosca started (incidence)		# of new Rosca started	# of Rosca auctions	# of Rosca participants	Pot value (in 1000 Rs.)
Unit of observation:	*Auction*	*Auction*	*Branch-Month*	*Branch-Month*	*Branch-Month*	*Branch-Month*	*Branch-Month*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Run-up Height							
Tsunami × after tsunami	0.004	0.000	−0.013	−0.015	−0.084	1.143	37.548
	(0.003)	(0.000)	(0.011)	(0.023)	(0.635)	(18.083)	(52.086)
P-value - bootstrapped S.E.	0.217	0.991	0.283	0.513	0.894	0.951	0.603
Confidence interval (95%)	[−0.006;0.014]	[−0.002;0.002]	[−0.042;0.027]	[−0.094,0.042]	[−3.656;1.319]	[−93.862;44.274]	[−198.504;112.411]
R-squared	0.180	0.028	0.322	0.330	0.978	0.984	0.970
Panel B: Damage Intensity							
Tsunami × after tsunami	0.003	0.000	−0.009	−0.018	−0.474	−9.868	0.369
	(0.003)	(0.000)	(0.011)	(0.021)	(0.678)	(19.334)	(52.536)
P-value - bootstrapped S.E.	0.446	0.588	0.421	0.371	0.489	0.601	0.994
Confidence interval (95%)	[−0.005;0.010]	[−0.001;0.001]	[−0.031;0.020]	[−0.065,0.026]	[−2.678;0.930]	[−70.540;31.615]	[−137.729;104.772]
R-squared	0.180	0.028	0.321	0.330	0.979	0.984	0.969
Mean of Dep.Var	0.330	0.011	0.357	0.721	63.617	2324.253	3623.295
Observations	19,594	19,955	308	308	308	308	308

Notes: Columns (1), (5), (6) and (7) are based on the main sample. Columns (2) to (4) are based on the main sample plus auctions from Roscas that started after the tsunami on December 26, 2004 that are excluded from the main sample due to selection concerns. Variables in columns (3) to (7) are aggregated per branch per month. Data from Rosca auctions in 14 branches from January 2004 to October 2005. Mean of dependent variables reported for the full sample. Month-of-auction and branch-denomination fixed effects are included in columns (1) and (2). Month-of-auction and branch fixed effects are included in columns (3) to (7). 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***
	(0.015)	(0.033)	(0.023)	(0.017)
Observations	12,855	12,855	12,855	12,855
Small pot size Roscas				
Estimated occupation share	0.069***	0.365***	0.477***	0.089***
	(0.012)	(0.056)	(0.049)	(0.020)
Observations	5,730	5,730	5,730	5,730
Large pot size Roscas				
Estimated occupation share	0.197***	0.482***	0.202***	0.119***
	(0.017)	(0.026)	(0.015)	(0.017)
Observations	7,125	7,125	7,125	7,125

Notes: Dependent variables: Dummy for occupational group j if auction is won by group j. Weighted OLS: h-weights correcting for imbalances over Rosca deciles and missing occupations included, see Section 3.3 for details. Sample includes all 12,855 observations for which the occupation is recorded. Data from Rosca auctions in 14 branches from January 2004 to October 2005. The sub-sample with small pot sizes includes 5,730 auctions from Roscas where the pot is worth Rs. 25,000 or less. The sub-sample with large pot sizes includes 7,125 auctions from 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

column 2), 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, Table 6, column 2). For self-employed and wage-employed members, these effects are precisely measured and confirmed by the damage intensity specification (Table 6, column 5). 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.

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. Our data confirms this claim: 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 (Table 5).[27] Conversely, institutional investors are much less frequent in large Roscas, where they account for only twenty percent of participants, relative to 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 (Table 6, column 4). In contrast, all point estimates are small and statistically insignificant at conventional levels in the sub-sample of Roscas with small pots (Table 6, column 3). 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

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

Table 6
Change in debt by occupational group.

Dependent variable: Debt (in 1,000 Rs.)	At baseline (1)	All (2)	Small pots (3)	Large pots (4)	All (5)	Small pots (6)	Large pots (7)
Occupation: Self-employed	9.744	Panel A: Run-up Height as tsunami measure			Panel B: Damage Intensity as tsunami measure		
	(10.535)						
Tsunami × after tsunami		21.918***	−0.061	32.778***	19.470***	0.277	29.094***
		(3.141)	(0.505)	(4.531)	(4.852)	(0.509)	(6.861)
P-value - bootstrapped S.E.		0.001	0.912	0.000	0.001	0.622	0.000
Confidence interval (95%)		[8.999;33.544]	[−1.130;2.859]	[14.012;48.107]	[5.301;29.350]	[−0.702;1.730]	[9.159;43.253]
R-squared		0.539	0.293	0.542	0.539	0.294	0.542
Occupation: Wage-employed	21.477						
	(27.783)						
Tsunami × after tsunami		−11.156**	−1.902	−16.075**	−11.232***	−2.185*	−16.147**
		(4.572)	(1.109)	(6.195)	(3.669)	(1.203)	(5.994)
P-value - bootstrapped S.E.		0.082	0.160	0.084	0.026	0.087	0.047
Confidence interval (95%)		[−27.136;5.280]	[−7.150;1.562]	[−37.584;9.814]	[−20.119;−2.388]	[−5.336;0.570]	[−30.217;−0.383]
R-squared		0.549	0.322	0.554	0.549	0.323	0.554
Occupation: Institutional investor	71.421***						
	(14.270)						
Tsunami × after tsunami		−12.107**	0.126	−18.289**	−6.772	0.334	−10.154
		(4.356)	(0.622)	(7.209)	(5.925)	(0.785)	(9.218)
P-value - bootstrapped S.E.		0.387	0.836	0.387	0.462	0.684	0.471
Confidence interval (95%)		[−18.614;13.142]	[−2.330;1.982]	[−29.000;21.694]	[−19.069;9.270]	[−1.751;2.298]	[−29.811;15.103]
R-squared		0.138	0.191	0.136	0.138	0.191	0.135
Occupation: Not employed	−7.500						
	(13.057)						
Tsunami × after tsunami		1.219	−1.707*	2.548	1.365	−0.927	2.567
		(5.692)	(0.889)	(8.261)	(4.259)	(0.974)	(6.131)
P-value - bootstrapped S.E.		0.752	0.646	0.705	0.761	0.636	0.737
Confidence interval (95%)		[−6.323;21.242]	[−3.146;1.746]	[−8.714;28.941]	[−6.098;14.428]	[−2.934;1.328]	[−8.252;20.763]
R-squared		0.158	0.199	0.163	0.158	0.196	0.163
Observations		12,855	5,730	7,125	12,855	5,730	7,125

Notes: Dependent Variable: Occupational group's debt: (incidence of winning the auction)*(0.5 - relative round of auction)*pot value. Weighted OLS: *h*-weights correcting for imbalances over Rosca deciles and missing occupations included, see Section 3.3 for details. The sample includes all 12,855 observations for which the occupation is recorded. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

primarily by a demand hike among entrepreneurs rather than a change in demand among any of the other occupational 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 column 1 of Table 6, only the institutional investor holds significant debt at baseline, worth Rs. 71,421 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.[28] 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 $ 526. This amount equals 75 percent of India's per capita GDP at the time (not purchasing-power-parity adjusted) and is equivalent to 40 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 $ 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 Eq. (8). 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 (Table 6, column 4) 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 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 pot size.

[28] 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 'institutional investor') participate in chit funds primarily with a borrowing motive.

Table 7
Price of credit.

	Winning bid		
	All auctions (1)	Small pots (2)	Large pots (3)
Panel A: Run-up Height			
Tsunami × after tsunami	0.260**	0.025	0.371**
	(0.098)	(0.117)	(0.158)
P-value - bootstrapped S.E.	0.049	0.836	0.083
Confidence interval (95%)	[0.001;0.623]	[−0.396;0.415]	[−0.087;0.923]
R-squared	0.455	0.397	0.425
Panel B: Damage Intensity			
Tsunami × after tsunami	0.195*	0.034	0.265
	(0.097)	(0.111)	(0.158)
P-value - bootstrapped S.E.	0.110	0.760	0.171
Confidence interval (95%)	[−0.071;0.441]	[−0.235;0.263]	[−0.184;0.670]
R-squared	0.455	0.397	0.425
Observations	19,594	8,285	11,309

Notes: Dependent Variable: Relative winning bid (percentage of the winning bid in the pot value of a Rosca). Weighted OLS: f-weights correcting for imbalances over Rosca deciles included, see Section 3.3 for details. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 an increase of 8.6 percent (Table 7, column 1). We only observe an increase in the winning bid in large pots (Table 7, column 3), which mirrors our findings regarding financial flows. Both patterns are consistent with a demand hike among entrepreneurs and only negligible demand changes, if any, among the other occupations.

The instantaneous price increase and the previously demonstrated reallocation of funds illustrate the simultaneous flexibility and rigidity of bidding Roscas as a 'middle-rung' financial 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 this segment of the financial market: Among all participants in the 78 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 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 Eq. (2) two indicators equal to one if the lender screens the borrower by recording her occupation (Table 8, column 1) or income (column 2), respectively. According to columns 1 and 2 of Table 8, Panel A, 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, which are not confirmed by the damage intensity measure in Panel B, however.

Second, we look at loan securitization. We estimate Eq. (2) 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, column 3 and 4 of Panel A).

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, columns 5 and 6 in Panel A). Conversely, there is only a small and insignificant negative effect on legal enforcement (Table 8, column 7 in Panel A). Hence, we conclude that loan securitization, enforcement and defaults did not change noticeably in response to the tsunami. If anything, screening of borrowers increased somewhat.

Taken together, our results are consistent with the view that the Roscas in our sample have generated larger gains from trade in response to the tsunami than usually accrue. We discard negative welfare effects of the tsunami on credit supply building on participants' revealed preferences for continued participation. First, no increase in defaults shows that staying in a Rosca has not become less attractive, even for members who have already won a pot, given that screening and collection efforts by the organizer are unchanged according to Table 8. Second, no increase in replacement of members who have not yet gotten a pot (Table 4) shows that staying in a Rosca has not become less attractive also for members who still await a pot. And while it may be objected that the continuing participation of the first group is driven by concerns about future access to credit, which may compensate welfare losses from current participation, at least for the second group this can be discarded: Members who withdraw from the Rosca before winning a pot are not blacklisted by the organizer. Third, the finding that the tsunami has no effect on demand for participation in Roscas started after December 2004 shows that the expected benefits from Rosca participation cannot have decreased. On the other hand, higher winning bids are an indication of increased gains from trade arising from the credit demand side in all models of bidding Roscas that have thus far been published (Besley et al., 1993; Calomiris and Rajaraman, 1998; Klonner, 2003; Kovsted and Lyk-Jensen, 1999; Kuo, 1993).

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 Eq. (10) 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

Table 8
Screening, loan securitization and default.

	Screening		Loan securitization		Default		
	Occupation recorded (1)	Income recorded (2)	Cosigner (incidence) (3)	Number of cosigners (4)	Arrear (incidence) (5)	Arrear amount (6)	Legal enforcement (incidence) (7)
Panel A: Run-up Height							
Tsunami × after tsunami	0.013**	0.012**	0.003	−0.003	0.004	0.001*	−0.005
	(0.005)	(0.005)	(0.004)	(0.012)	(0.004)	(0.001)	(0.006)
P-value - bootstrapped S.E.	0.181	0.230	0.452	0.839	0.258	0.148	0.416
Confidence interval (95%)	[−0.008;0.025]	[−0.010;0.020]	[−0.010;0.018]	[−0.039;0.037]	[−0.003;0.019]	[−0.002;0.003]	[−0.033;0.005]
R-squared	0.151	0.266	0.241	0.349	0.136	0.131	0.182
Panel B: Damage Intensity							
Tsunami × after tsunami	0.009	0.007	0.001	−0.006	0.003	0.001	−0.007
	(0.006)	(0.006)	(0.004)	(0.011)	(0.004)	(0.001)	(0.006)
P-value - bootstrapped S.E.	0.232	0.319	0.757	0.608	0.559	0.342	0.358
Confidence interval (95%)	[−0.008;0.023]	[−0.009;0.020]	[−0.008;0.011]	[−0.031;0.022]	[−0.005;0.013]	[−0.001;0.002]	[−0.024;0.008]
R-squared	0.150	0.265	0.241	0.349	0.136	0.131	0.183
Observations	19,594	12,960	12,960	12,960	12,960	12,960	12,960

Notes: In columns (2) to (7), the sample is restricted to the 12,960 recipients of pots other than the institutional investor, see Table 2. Weighted OLS: f-weights correcting for imbalances over Rosca deciles included, see Section 3.3 for details. 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 9
Change in debt by occupational group, placebo-experiment (2003 and 2004).

Dependent variable: Debt (in 1,000 Rs.)	All (1)	Small pots (3)	Large pots (4)	All (2)	Small pots (5)	Large pots (6)
	Panel A: Run-up Height as tsunami measure			Panel B: Damage Intensity as tsunami measure		
Occupation: Self-employed						
Pseudo-Tsunami × after pseudo-tsunami	−8.486	0.235	−13.865	−6.809*	0.391	−11.035
	(4.902)	(0.518)	(9.334)	(3.707)	(0.472)	(6.774)
P-value - bootstrapped S.E.	0.427	0.675	0.467	0.111	0.462	0.156
Confidence interval (95%)	[−15.635;8.695]	[−1.356;2.345]	[−28.145;15.442]	[−15.667;1.821]	[−0.677;1.600]	[−28.817;3.660]
Observations	14189	6409	7780	14189	6409	7780
R-squared	0.231	0.100	0.239	0.231	0.100	0.239
Occupation: Wage-employed						
Pseudo-Tsunami × after pseudo-tsunami	−3.050	−1.160	−2.773	−2.870	−1.843	−1.813
	(3.524)	(1.066)	(5.890)	(4.412)	(1.084)	(7.238)
P-value - bootstrapped S.E.	0.377	0.252	0.649	0.556	0.124	0.832
Confidence interval (95%)	[−14.961;8.821]	[−7.985;1.640]	[−15.825;20.185]	[−13.934;8.089]	[−5.458;0.506]	[−18.069;15.962]
Observations	14189	6409	7780	14189	6409	7780
R-squared	0.341	0.343	0.349	0.341	0.344	0.349
Occupation: Institutional investor						
Pseudo-Tsunami × after pseudo-tsunami	−0.140	−1.351	1.683	1.135	−0.417	3.128
	(1.483)	(1.193)	(2.179)	(1.832)	(1.207)	(2.422)
P-value - bootstrapped S.E.	0.931	0.583	0.433	0.655	0.759	0.237
Confidence interval (95%)	[−2.316;7.332]	[−3.873;3.329]	[−1.730;10.970]	[−2.144;8.319]	[−2.970;2.618]	[−1.452;12.049]
Observations	14189	6409	7780	14189	6409	7780
R-squared	0.374	0.219	0.374	0.374	0.218	0.374
Occupation: Not employed						
Pseudo-Tsunami × after pseudo-tsunami	2.845*	0.313	4.597	2.563*	0.402	3.663
	(1.418)	(0.476)	(2.634)	(1.373)	(0.481)	(2.690)
P-value - bootstrapped S.E.	0.128	0.523	0.172	0.131	0.421	0.250
Confidence interval (95%)	[−2.176;8.273]	[−1.306;2.358]	[−5.751;13.229]	[−0.918;5.697]	[−0.687;1.688]	[−3.707;9.681]
Observations	14189	6409	7780	14189	6409	7780
R-squared	0.177	0.167	0.183	0.177	0.167	0.183

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

effects in such a placebo estimation as no disaster took place at the time of the artificially created event.

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 small positive effects are obtained 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. Similarly, placebo experiments with the dependent variables attrition, supply and market size, price of credit, and screening, loan securitization and default do not yield any significant estimates (see Tables C.3, C.4, and C.5 in Appendix C). 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 and 3 for the run-up height (Panel A) and damage intensity (Panel B) tsunami intensity measure). Second, we increase the distance to 50 kilometers, which increases the number of branches to 25 (Table 10, column 4). 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). By excluding near-coastal branches, we assess the possibility of spillover effects from coastal to near-coastal locations.

Table 10 sets out the results for our main definition of coastal branches (columns 1) 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 wave did not reach them physically. All in all, our results are remarkably robust to alternative definitions of the sample.[29]

6. Conclusion

In this study, we investigate responses of Roscas 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 Roscas in Tamil Nadu. Given the inelastic credit supply of Rosca credit in the short run, we analyze how credit flows between occupational groups, the price of credit, loan securitization and defaults 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 responses in these credit networks is facilitated by the flexible auction allocation mechanism, a non-market element of bidding Roscas. In contrast to the wide-spread skepticism regarding the potential of traditional credit and insurance networks for mitigating the effects of seemingly aggregate shocks, our results suggest that commercial Roscas, an eminent example of a middle-rung financial institution that combines elements of both formal and informal finance, 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 here provided urgently-needed funds to 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 sanctioned several relief packages to replace productive assets and to reconstruct infrastructure and residences, and also made available additional credit, through government loan schemes and self-help groups. But most of these measures either arrived late, with a time lag of several months (Government of Tamil Nadu, 2005a), or were insufficient (Government of Tamil Nadu, 2008). This underlines the importance of the flexibility and swift responsiveness of the financial networks studied here as a disaster coping mechanism.[30]

Our findings highlight the role of Roscas, a popular indigenous financial institution in many low- and middle-income countries, for dealing with economic risks when other segments of the financial market fail and the government does not or cannot intervene quickly enough. They challenge the common view that local, network-based schemes fail to insure seemingly aggregate shocks and highlight that shocks which appear aggregate in nature, such as natural disasters, comprise substantial idiosyncratic components. 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 Rosca credit as a coping mechanism for such shocks. In addition, to explore how Roscas and other similar networks could be leveraged to efficiently channel external relief aid to households and enterprises seems a worthwhile avenue for future research and policy.

Data availability

Data and code will be made available by the authors upon request.

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Appendix A. Proofs

Proposition 1

Axioms 1 through 4 taken together imply that Eq. (3) can be written as the system of T non-linear equations

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

with the $T-1$ unknowns $r_1, \ldots, r_{T-1}$. The discount factor r_T does not appear in this system because $(1 + r_T)$ is always raised to the power zero in (A.1). Denoting by $1\{A\}$ the indicator function, which equals one if logical statement A is true and zero otherwise, this system of

[29] The same holds true for our analysis of the tsunami's effect on the price of credit, which is also robust to these alternative sample definitions (results available upon request).

[30] We elaborate on this issue in a companion paper, which is in preparation.

Table 10
Change in debt by occupational group, alternative definitions of near-coastal locations.

Definition of coastal branches:	0–25 km	0–15 km	0–20 km	0–50 km	0–5 & 15–25 km
	(1)	(2)	(3)	(4)	(5)
Panel A: Run-up Height as tsunami measure					
Occupation: Self-employed					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.539	0.585	0.560	0.498	0.571
Occupation: Wage-employed					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.549	0.364	0.571	0.474	0.542
Occupation: Institutional investor					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.138	0.148	0.139	0.144	0.143
Occupation: Not employed					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.158	0.133	0.132	0.179	0.165
Number of clusters	14	11	12	25	8
Panel B: Damage Intensity as tsunami measure					
Occupation: Self-employed					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.539	0.585	0.560	0.498	0.571
Occupation: Wage-employed					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.549	0.364	0.571	0.474	0.542
Occupation: Institutional investor					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.138	0.147	0.138	0.143	0.142
Occupation: Not employed					
Tsunami × 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	12,855	9,678	10,005	20,413	8,592
R-squared	0.158	0.133	0.132	0.179	0.165
Number of clusters	14	11	12	25	8

Notes: See Table 6.

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 $a_{ij} = 1\{i=j\}\widetilde{Pot}_i - \frac{1}{T}\widetilde{Pot}_j$, $x_j = (1+r_j)^{T-j}$, and b_i equals Pot/T for $i < T$ and $-\frac{T-1}{T}Pot$ for $i = T$, $i = 1,\dots,T$, $j = 1,\dots,T-1$. Noticing that x_j is strictly increasing in r_j for all $j = 1,\dots,T-1$, a unique solution to $Ax = b$ will deliver the unique solution of (A.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^*, $i = 1,\dots,T-1$, 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 (A.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 (A.1). ■

Proposition 2

For Eq. (4) notice from Proposition 1 that

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

For Eq. (5), we depart from the third line of the proof just given, and notice that $1\{t=i\}=x_{it}$,

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

The mean of x, $\frac{1}{T}\sum_{t=1}^{T} x_{it}$, just equals $\frac{1}{T}$. Viewing the vectors $(x_{i1},1)$, $\dots,(x_{it},t),\dots,(x_{iT},T)$ as a bivariate data sample, from the properties of empirical covariances it follows that, in (A.2), $(T-t)$ can be substituted by $-t$ and that instead of subtracting $\frac{1}{T}$ from x_{it}, we may add $\frac{1}{T}\sum_{t=1}^{T} t = \frac{T+1}{2}$ 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 Eq. (4) for all members of A. The second formula follows from adding the left and right hand sides of Eq. (5) for all members of A. ■

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 Eq. (2) 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

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

where k indexes occupations, $n^k_{\dots,dec}$ 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 data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2022.102996.

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