2010

Separate and Unequal: Post-Tsunami Aid Distribution in Southern India

Daniel P Aldrich, *Purdue University*

	SSQU	736	B	Dispatch: 20.8.10 Journal: SSQU	CE: Sukanya
	Journal Name	Manuscript No.		Author Received: No. of pages: 21	PE: Leelakshi/Jay

Separate and Unequal: Post-Tsunami Aid Distribution in Southern India*

Daniel P. Aldrich, *Purdue University*

Objective. Disasters are a regular occurrence throughout the world. Whether all eligible victims of a catastrophe receive similar amounts of aid from governments and donors following a crisis remains an open question. *Methods.* I use data on 62 similarly damaged inland fishing villages in five districts of southeastern India following the 2004 Indian Ocean tsunami to measure the causal influence of caste, location, wealth, and bridging social capital on the receipt of aid. Using two-limit tobit and negative binomial models, I investigate the factors that influence the time spent in refugee camps, receipt of an initial aid packet, and receipt of 4,000 rupees. *Results.* Caste, family status, and wealth proved to be powerful predictors of beneficiaries and nonbeneficiaries during the aid process. *Conclusion.* While many scholars and practitioners envision aid distribution as primarily a technocratic process, this research shows that discrimination and financial resources strongly affect the flow of disaster aid.

Research has demonstrated that the provision of foreign aid to developing countries under standard circumstances is biased; that is, nation-states rarely provide loans, grants, and technical assistance in solely apolitical ways. Instead, the size (in terms of population) of the recipient, its connections to the giver, and other political factors matter (Dowling and Hiemenz, 1985; Arvin, Piretti, and Lew, 2002). Given these findings in the international arena, many have argued that post-disaster aid, whether distributed domestically by nongovernmental organizations or by the national government, reaches certain groups and victims while bypassing others (Martin, 2005; Gill, 2007). On the other hand, NGOs and state governments insist that distribution is or should be solely based on need (Brookings-Bern, 2008).

*Direct correspondence to Daniel P. Aldrich, Department of Political Science, Purdue University, 100 N. University St., West Lafayette, IN 47907 ⟨daniel.aldrich@gmail.com⟩. Daniel P. Aldrich will share all data and coding information with those wishing to replicate the study. Mr. M. Louis and People's Watch Tamil Nadu worked tirelessly to procure much of the data used in this analysis; the author gratefully acknowledges their efforts and generosity in sharing their data. The author conducted the relevant fieldwork, archival research, and interviews in Tamil Nadu, India for this article while on an Abe Fellowship from the Center for Global Partnership and the Social Science Research Council during 2007–2008. He thanks Janki Andharia, Lokesh Gowda, Jacquleen Joseph, and Sunil Santha with the Tata Center for Disaster Management within the Tata Institute of Social Sciences, Annie George with the Nagapattinam Coordination and Resource Centre, and Hari Ayyappan for their help while in the field. Finally, Jay McCann and four anonymous reviewers provided valuable advice.

SOCIAL SCIENCE QUARTERLY, Volume 91, Number 5, December 2010

The 2004 Indian Ocean tsunami provides a tragic "natural experiment" for investigating the patterns of aid provision to affected villages and communities. Using a new data set on 62 similarly damaged, inland fishing villages (also known as "non-ocean-fishing communities") across coastal southeast India, this article underscores the role played by caste, regional governance, family status, and other factors in the receipt of aid.

On December 26, 2004, two undersea earthquakes triggered the Indian Ocean tsunamis that devastated much of Southeast Asia, killing and making homeless hundreds of thousands of residents across the area. Estimates of the death toll range higher than 300,000 for the nations of India, Indonesia, Thailand, and Sri Lanka; the waves were powerful enough to reach Strusbaai, South Africa. In India alone, more than 12,000 people perished, with three-quarters of the fatalities being women and children caught by the up to 30-foot tall waves. For the first two days following the wave, villagers worked together to pull survivors and bodies from the wreckage, seek higher ground, and treating the wounded. The Government of India soon intervened with the help of domestic and international nongovernmental organizations (NGOs) to provide relief supplies, medical assistance, and temporary housing to the survivors. In this chaotic environment, government officials sought to assist as many victims as they could.

Observers argued that the reaction from the international relief community to the Indian Ocean tsunami was "the most publicized and best-funded response of all times" (Alexander, 2006:5). While a number of Western nations had immediately pledged financial and medical assistance, "[t]he US soon increased its contribution to $950 million, Germany pledged 727 million, Australia 830 million, France 443 million, Japan 300 million, Britain 120 million, China 83 million" (Bindra, 2005:181). While Naomi Klein (2007) has dubbed the phenomenon in which large corporations and U.S. contractors profit from crisis as "disaster capitalism," the organizations building houses, repairing roads and bridges, and assisting villagers in the recovery were on the whole not U.S.-based corporations. However, this tremendous outpouring of aid brought with it a number of often unexpected externalities. Local NGOs referred to the aid that flowed in as a "second tsunami" (Nelson, 2007) due to the damage it did to social and traditional economic structures in coastal India.

The Government of India, NGOs, and councils sought to coordinate their efforts to distribute the massive amount of aid to tens of thousands of victims. Observers praised the Government of India for handling the disaster "admirably" (Salagrama, 2006:55) as it "went about the rehabilitation programmes in a transparent manner by putting all relevant information on the Internet and updat[ing it] frequently" (Salagrama, 2006:55). Other assessments of the aid and relief distribution processes were more mixed: "Though the relief coordination with NGOs and government local system worked well at the initial stage, aid did not reach to the most vulnerable communities like Dalits, tribals, differently-abled people, senior citizen, widows and women in general'' (Chandran, n.d.). In its post-disaster overview of the recovery, the U.N. Team for Tsunami Recovery Support admitted to problems due to ''unequal distribution'' (2007:14). Some saw any problems in distribution as localized, and not more systematic: ''There were instances (in Kanyakumari) where members of particular groups were reportedly discriminated against in rehabilitation programmes'' (Salagrama, 2006:62).

Local and international observers, however, soon argued that they had evidence of what they labeled ''systematic discrimination'' in the provision of supposedly guaranteed aid—everyone who was eligible to receive supplies and cash assistance did not do so, especially among peripheral groups. The NGO SNEHA (Social Needs Education and Human Awareness) documented stories of many survivors of the tsunami who lost family members but did not receive compensation from the government (SNEHA, 2006:20). Human Rights Watch (2007) detailed systematic discrimination against the Scheduled Castes—often referred to as Untouchables or Dalits—in two different recoveries in India, including the 2001 Gujarat earthquake and the 2004 Indian Ocean tsunami. Similarly, Louis (2005) listed the names of nearly 8,000 individuals—most of them Dalits—eligible for compensation and assistance from the government who did not receive it. Many critics have argued that aid was overprovided to coastal fishing communities in the area, while inland, non-ocean-fishing villages were left out.

The Government of India set up multiple aid policies after the tsunami. Families initially received food, equipment, and clothing to help them in the immediate post-tsunami period (aid known as the ''relief package''), followed by money for those who had lost loved ones, homes, or jobs, and, over time, payments to assist them in the rebuilding period. In interviews with social workers from the Mumbai-based Tata Institute of Social Science, a number of victims stated that they had not received compensation from the government despite being eligible for it. For example, one resident reported that ''I am from a Dalit community. So far I didn't get any tsunami relief materials. Ours is also a tsunami affected area. Now, due to the entry of the salt water our agricultural fields are destroyed and we lost our livelihood . . . But still I didn't get any benefit.'' National and local government officials worked with local institutions to set up temporary refugee camps on higher ground where families and individuals could stay until they could return to their homes, which were often damaged. Some, like Lourdamma, a widow from the village of Keelamanakudi, were in a relief camp for a week, while others, such as Mr. Nainappan, from Kallar, spent only a day or so away from their village.

This article tests which factors affected three different post-tsunami policies providing relief and assistance at the village level by the Government of India with the assistance of NGOs: the length of time (measured in days) spent in the relief camps, the percentage of eligible families receiving the initial bundle of relief supplies, and the percentage of eligible families receiving 4,000 rupees in assistance. These three policy outcomes displayed high levels of variation as can be seen in the descriptive statistics provided in Table 1. This article seeks to understand why survivors in some of the 62 villages stayed in refugee camps for days while others stayed for weeks, and why some villages had more than their registered number of families receiving assistance while in others only three-quarters of eligible families received anything.

Theories Explaining Aid Access

Scholars of catastrophe have suggested a number of factors that may influence how aid is distributed and received by survivors; while the six factors detailed below may not be exhaustive, they cover the core concerns raised by past research, aid practitioners in the field, and the survivors to whom I spoke.

Many government agencies and decisionmakers see the provision of disaster aid as—at least ideally,[1] if not in practice—an **apolitical** process in which the distribution is based on need, and not on other factors such as minority status, location, wealth, and so on. The Federal Emergency Management Agency (FEMA) states that ''[a]ny person eligible to receive disaster aid or other services from FEMA is entitled to those benefits without discrimination'' based on Title VI of the U.S. Civil Rights Act of 1964. Similarly, Article 2 of the Principles of Conduct for the International Red Cross states that: ''Aid is given regardless of the race, creed or nationality of the recipients and without adverse distinction of any kind. Aid priorities are calculated on the basis of need alone'' (quoted in Bakewell, 2001:6). One manual for disaster relief stated that: ''The principles of equality and non-discrimination . . . should underpin all disaster relief, recovery and reconstruction efforts'' (Brookings-Bern, 2008:10). After the disaster, every family whose house and/or belongings were destroyed by the tsunami should have received a single initial aid package, while affected families should further have received distributions of 4,000 rupees.

Apolitical, equitable distribution may have been the goal; however, empirical evidence contradicts such optimism. Instead, scholars have argued that the resources available to community members before the disaster or crisis strongly determine the community's ability to extract assistance following the crisis. Hence the **wealth** of the village may determine how many of its inhabitants eligible for aid actually received it as it serves as a proxy for legitimacy and education. Survivors with more wealth may be better po-

[1] Some might argue that the existence of ''social development advisors'' with organizations such as Britain's Joint Funding Scheme with Official Development Assistance (Wallace, 1997:42) and the Department for International Development (DFID) is evidence that foreign donors recognize that aid provision and receipt has not been sufficiently ''objective.'' Whether or not this is also the pattern post-tsunami requires empirical investigation.

TABLE 1

Descriptive Statistics of Full Data Set

Variable	*N*	Mean	*SD*	Min	Max
Duration in relief camps (days)	61	18.61	29.12	0	210
Percentage of eligible families receiving relief supplies	62	0.96	0.25	0	1.69
Percentage of eligible families receiving 4,000 Rs compensation	43	0.85	0.31	0	1
Nagapattinam District (dummy)	62	0.48	0.50	0	1
Cuddalore District (dummy)	62	0.24	0.43	0	1
Thiruvallur District (dummy)	62	0.13	0.34	0	1
Kanyakumari District (dummy)	62	0.14	0.35	0	1
Scheduled Tribe percentage	62	0.09	0.28	0	1
Scheduled Caste percentage	62	0.56	0.47	0	1
Most Backwards Caste percentage	62	0.22	0.40	0	1
Homed owned per family	62	1.03	0.22	0.66	1.97
Homes owned per capita	62	0.26	0.05	0.14	0.39
Percentage of families making between 0 and 500 Rs per week	62	0.75	0.41	0	1.00
Contact only with the Government of India	62	0.13	0.34	0	1
Contact only with NGOs, private organizations, political parties, or the villagers themselves	62	0.66	0.48	0	1
Contact with the government and at least one other group	62	0.21	0.41	0	1

sitioned due to their financial resources and recognized authority to contact NGOs, aid agencies, and government officials through informal or formal channels, and hence can better ensure aid receipt. Alternatively, households with more wealth may be better educated and better able to follow the often complex procedures of aid distribution than poorer and less educated residents.

Related to wealth is the **structure of the families** in the affected area. Traditionally, rural Indian families lived in joint family structures in which extended members dwelled together under the same roof. In the past decades, cultural practices have created a social environment in which nuclear families—not extended ones—are becoming the norm. While greater numbers of individuals in joint families create situations in which multiple generations of families share homes (and hence there are fewer homes owned per family), aid policies may be built on assumptions that single families sharing one home are the standard. Hence aid may be less likely to be delivered to multiple families living in the same household.

Rather than being a technocratic process or one based on the socioeconomic or family conditions of the village, the ability of the villagers to connect with extra-local organizations—regardless of wealth—may instead be crucial (Szreter and Woolcock, 2004:655). Hence the amount of **linking**

social capital held by the residents may determine access to government and NGO resources. Wetterberg (2004) demonstrated that in Indonesia, households tied into external organizations were better able to access resources after the devastating shock of the Asian financial crisis. Linking social capital, which transcends geographical distance and social hierarchy, can assist even resource-poor areas in drawing attention to their plight (Szreter, 2002). In Thailand, villages with linking social capital created connections and alliances with elites to influence public policy (Birner and Wittmer, 2003). Similarly, Indian hamlets unable to attract visitors, NGOs, and government officials to view damage to their villages were not provided with assistance following the tsunami (Praxis Institute for Participatory Practices, 2006).

Another critical factor in the aid distribution may be **location**. The affected area itself may be envisioned as being more (or less) needy based on damage from the catastrophe, it may have stronger native governance institutions, or it may be easier (or more difficult) to reach via standard roads and transport networks. Damaged or destroyed villages in certain regions may not be seen as "needy" following a disaster; some areas "received less attention as the focus had been mainly on the worst affected districts like Cuddalore and Nagapattinam" (Salagrama, 2006:22). Other communities may be far removed from standard transportation systems, so that "in other communities, particularly remote ones, the distribution of aid seemed to be quite slow and limited" (Rodriguez et al., 2006:170). Local activists argued that Nagapattinam had stronger governance institutions pre-tsunami, which allowed a flourishing of NGOs post-tsunami, such as the Tamil Nadu Tsunami Resource Centre (TNTRC) in Chennai and the Nagapattinam Coordination and Resource Centre (NCRC) (Interviews, February 2008).

Finally, ethnic and/or racial discrimination may play a role in the distribution of aid post-disaster. In India, **the caste system**, with Scheduled Tribes and Scheduled Castes (abbreviated in Indian records as ST and SC) as the lowest castes on the "ladder" and with Backwards Castes and Most Backwards Castes (BC and MBC) as the middle castes may influence how officials and local officers provide aid (REDS, 2006:16).[2] Some charged that "[a]cross the backwaters, NGOs are moving in to assist fishing communities but they do not cross over to this tribal hamlet or the nearby Dalit community" (Martin, 2005:44). Other observers of the post-tsunami recovery argued that caste discrimination was an "unquestionable fact. The testimo-

[2]A full description of the Indian caste system is beyond the scope of this article, but in broad strokes, the Indian Constitution set up official categories for the population groups previously known as Untouchables (with Scheduled Castes often referred to as *Dalits* and Scheduled Tribes as *Adivasis*). The government reserves a certain proportion of positions in public-sector employment for these groups. In the district of Kanyakumari, unlike the other coastal regions under discussion here, the backwards castes and most backwards are usually Christians, not Hindus (REDS, 2006:24). See Mines (2009) for a broader discussion of caste.

nies of Dalit victims of the tsunami all along the Indian coast of Tamil Nadu show remarkable consistency, pointing to a systematic and predictable type of discrimination'' (Gill, 2007:7). Given the variety of factors that may affect how aid is distributed to survivors, this article now uses data from a sample of villages hit by the tsunami to illuminate patterns in access to assistance.

Data

This article uses a quantitative data set created by M. Louis and his researchers made up of 62 noncoastal fishing hamlets and villages most strongly affected by the tsunami; the unit of analysis is the hamlet or village (Louis, 2005).[3] Louis selected these localities because they should have received aid from the government due to the damage done to them by the tsunami. By deliberately selecting observations ''across a range of values of the dependent variable,'' the team utilized a choice-based sampling method (King, Keohane, and Verba, 1994:141) rather than using a larger, completely random sample. Observers categorized these villages as marginalized, vulnerable, and hard-hit by the disaster. Residents of these villages worked in a variety of occupations, including backwater fishing, shell collection, pearl collection, algae collection, lime powder production, ornamental shell manufacturing, and seasonal agriculture (Louis, 2005:9). Actual levels of aid receipt varied across villages; the research team did not know levels of receipt when they chose villages for the study. Louis and his sampling team spent 80 person-days in the villages in July 2005 gathering data through transect walking, social, resource, and livelihood mapping, and questionnaires (Louis, 2005:3–7).

The existing variables within the data set match up well with the theories detailed previously about distribution patterns. Wealth is captured through the number of homes owned per capita and the percentage of families making between 0 and 500 rupees per week. Family structures are measured through the average number of homes owned per family in the village (with nuclear families having higher scores and extended families lower ones). Levels of social capital are captured through the village's connections to the outside world—specifically, whether or not the village had contact solely with government officials, solely with nongovernment sources (such as NGOs, the villagers themselves, private donors, etc.), or with a mix of the two. Location information for each village was captured by dummy variables for Nagapattinam District, Cuddalore District, or Thiruvallur District. Finally, caste was measured through percentage of the village in the Scheduled Tribe, Scheduled Caste, and Most Backwards Caste categories.

[3]These villages may indeed define communities ''sidelined'' in the relief process; exactly who received what in these marginalized, peripheral hamlets has not yet been investigated quantitatively and data on these outcomes provides empirical evidence for broader patterns of aid delivery.

Methodology

All the regression models here seek to untangle the effects of individual variables from potentially confounding factors. The three dependent variables under investigation—the length of time (measured in days) spent in the relief camps, the percentage of eligible families receiving the initial bundle of relief supplies, and the percentage of eligible families receiving 4,000 rupees in assistance—require nonstandard models because each variable is dispersed or censored differently.

When dealing with a count variable (i.e., a positive dependent variable bounded at zero), standard ordinary least squares (OLS) models are inappropriate. Instead, the general class of event-count models, including the Poisson model and negative binomial models, are most appropriate. Given the overdispersal of the dependent variable—the number of days spent in camps—the negative binomial model better fit the data than the Poisson. Similarly, standard OLS models are inappropriate when dealing with a bounded or censored dependent variable such as percentages. Wooldridge (2006:596) points out that if scholars used an OLS model, "we would possibly obtain negative fitted values, which leads to negative predictions for y" and would additionally provide inconsistent estimates of beta coefficients. Rosett and Nelson (1975) developed the mathematics behind a more appropriate model for percentages, known as a censored regression model or a "two-limit tobit." Long (1997:189, 212) shows how the "two limit tobit model uses all of the information, including information about the censoring, and provides consistent estimates of the parameters," which can be applied when "the outcome is a probability or a percentage." Therefore, the two main approaches used for analyzing the data set are two-limit tobit and negative binomial models.

Next, rather than relying on long lists of hard-to-interpret coefficients (although coefficient tables are provided throughout the text), this article uses simulations and confidence intervals to better illustrate its quantities of interest. Simulations together with confidence intervals extract and present information about the variables under investigation and estimate the degree of uncertainty in predictions generated by these analyses. In a simulation, we learn about the distribution of our data by taking many random draws from it and estimating the parameters in the actual population in a way that accounts both for sampling error and fundamental uncertainty (Tomz and Wittenberg, 1999). I created 1,000 simulations of the main and ancillary parameters and then displayed the predicted outcomes bounded by 95 percent confidence intervals (King, Tomz, and Wittenberg, 2000).

Results: Number of Days in Relief Camps

Following the tsunami, survivors in Tamil Nadu (and elsewhere) fled their homes to seek shelter on higher ground. Some villages spent only a short

TABLE 2

Estimated Coefficients

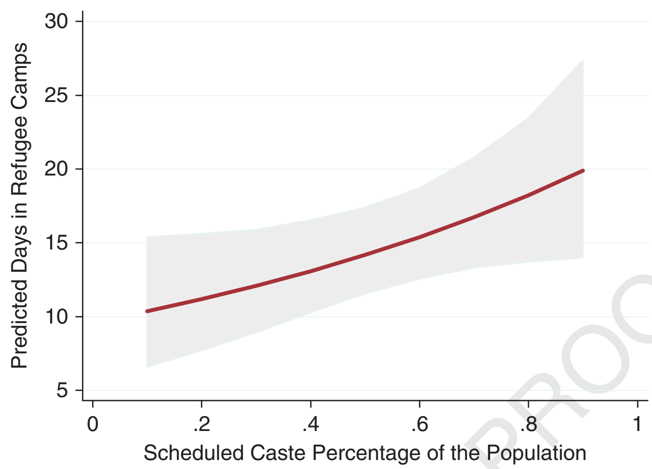
Dependent Variable: Duration in Refugee Camps (Days)	Negative Binomial (IRR)
Nagapattinam District (dummy)	0.29***
	0.12
Cuddalore District (dummy)	0.33***
	0.14
Thiruvallur District (dummy)	0.13***
	0.07
Kanyakumari District (dummy)	(omitted)
Scheduled Tribe percentage	1.05
	0.65
Scheduled Caste percentage	2.29**
	0.91
Most Backwards Caste percentage	1.93
	0.89
Homed owned per family	2.20
	1.39
Percentage of families making between 0 and 500 rupees per week	1.28
	0.39
Contact only with the Government of India	1.06
	0.41
Contact only with NGOs, private organizations, political parties, or the villagers themselves	0.83
	0.27
Contact with the government and at least one other group	(omitted)
/lnalpha	– 0.49
	0.19
Alpha	0.61
	0.12
N	61

NOTE: ***$p<0.01$; **$p<0.05$; *$p<0.1$. Standard errors are listed beneath the estimated coefficients. Variables are omitted to avoid the "dummy variable trap," which would otherwise create perfect multicollinearity.

time in these refugee camps, while others spent weeks or even months in them. All the villages in this study suffered significant amounts of damage to their homes (Louis, 2005). An important question is why villages with similar amounts of damage would not return home at the same time. Based solely on the negative binomial regression results, proxies for location and Scheduled Caste proved to be both significant and important in predicting the amount of time spent in refugee camps, but followup with simulations proved that only caste remained significant. Table 2 provides the estimated coefficients, standard errors, and significance of the full list of proxies. Figures 1 and 2 display the relationship between caste, location, and interval in the relief camps.

FIGURE 1

Caste as a Strong Predictor of Duration in Relief Camps



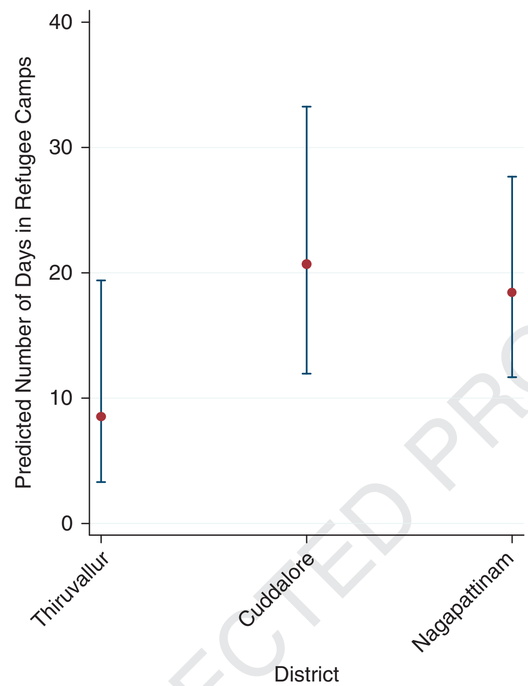
NOTE: $N = 61$, simulations = 1,000. All other variables held at their means except for Scheduled Caste percentage of the population, which varied. The gray outline indicates the 95 percent confidence interval around the predicted value.

Figure 1 illustrates that the greater the percentage of Scheduled Caste (SC) individuals within the village, the longer the village members' stay in relief camps, holding all other variables—including location, wealth, family structure, damage, and so forth—at their means. According to these simulations, a village that had with less than 20 percent of its residents as Scheduled Caste members would be expected to stay approximately 10 days in the camp, while a similar village with 80 percent or more Scheduled Caste members would stay closer to three weeks in the camp. The gray outline around the predicted variable line is wider where predicted outcomes are less certain, and narrower where there is more information (observations). The confidence intervals confirm the overall trend that villages that had more SC members remained in the refugee camps for longer periods of time.

Figure 2 shows that survivors from villages in the districts of Nagapattinam, Cuddalore, and Thiruvallur are predicted to spend 18, 21, and 9 days in refugee camps, respectively. However, the 95 percent confidence intervals surrounding these predictions overlap. This indicates that based on this moderate-sized sample of cases, we cannot dismiss the null hypothesis that—holding all other variables at their means—the location of the village was *not* a critical factor in determining the length of time spent in refugee housing.

FIGURE 2

No Evidence that Location Serves as Predictor of Duration in Relief Camps



NOTE: $N = 61$, simulations = 1,000. All other variables held at their means except for location of village, which varied. Vertical lines represent the 95 percent confidence interval around the predicted value, which is represented by the dot. Where lines overlap, we are unable to statistically distinguish between the predictions.

This finding is important because many observers may intuitively believe that Nagapattinam residents would spend more time in the camps because of perceptions of severe damage done to this region (Louis, 2005:17). However, reported tsunami damage levels across these 62 villages were quite similar, so we cannot rely on this belief alone. Further, while conditions in some temporary shelters—such as those in Thiruvallur—may have been quite poor (Fritz Institute, 2005:4; Martin, 2005) due to inappropriate construction materials, and while some argued that certain fishing villages deliberately spent more time outside their homes in order to draw in more attention (Bavinck, 2008), these data do not support these factors as ones that systematically altered the length of refugee camp stays. Location and other variables thought important did not measurably alter the length of stay, whereas caste did.

Results: Percentage of Eligible Families Receiving Relief Supplies

Having explored why certain villages spent more time in relief camps than others, I next explore the percentage of eligible families who received the initial relief packet from the government. As mentioned previously, if the apolitical approach to distribution were actually carried out, the percentage of eligible families receiving aid should be 100 percent—and it was not. Table 3 lists the estimated coefficients for the variables that influenced what portion of eligible families receive the relief packet, and Figures 3 and 4 display simulations generated from these data. Based on these estimated coefficients, villages located in Nagapattinam were more likely than their

TABLE 3

Estimated Coefficients

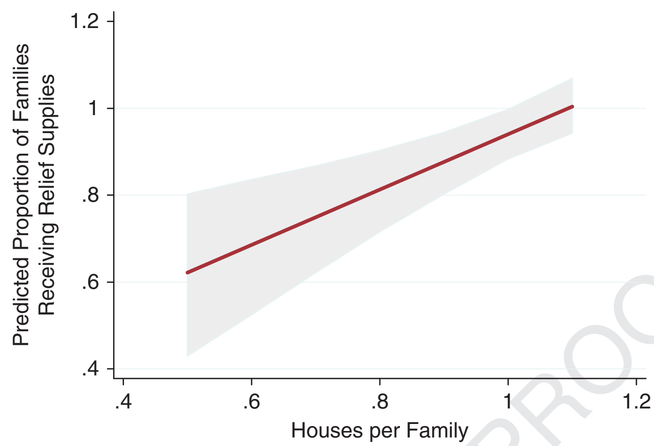
Dependent Variable: Percentage of Eligible Families Receiving Relief Supplies	Two-Limit Tobit
Nagapattinam District (dummy)	0.197**
	0.10
Cuddalore District (dummy)	0.15
	0.10
Thiruvallur District (dummy)	−0.22*
	0.13
Kanyakumari District (dummy)	(omitted)
Scheduled Tribe percentage	0.09
	0.14
Scheduled Caste percentage	0.06
	0.11
Most Backwards Caste percentage	0.02
	0.12
Homes owned per family	0.679***
	0.17
Percentage of families making between 0 and 500 rupees per week	−0.02
	0.08
Contact only with the Government of India	−0.165*
	0.09
Contact with the government and at least one other group	−0.07
	0.08
Contact only with NGOs, private organizations, political parties, or the villagers themselves	(omitted)
Constant	0.16
	0.20
/sigma	0.22
	0.02
N	62

NOTE: ***$p<0.01$; **$p<0.05$;

*$p<0.1$. Standard errors are listed beneath the estimated coefficients. Variables are omitted to avoid the "dummy variable trap," which would otherwise create perfect multicollinearity.

FIGURE 3

Family Structure as a Predictor of Propensity for Receiving Relief



NOTE: $N = 62$, simulations = 1,000. All other variables held at their means while houses per family varied. The gray outline indicates the 95 percent confidence interval around the predicted value.

counterparts in other districts to receive this aid—perhaps because of the better organization of the local governance structures and the umbrella organizations that mobilized the NGO response in this area.

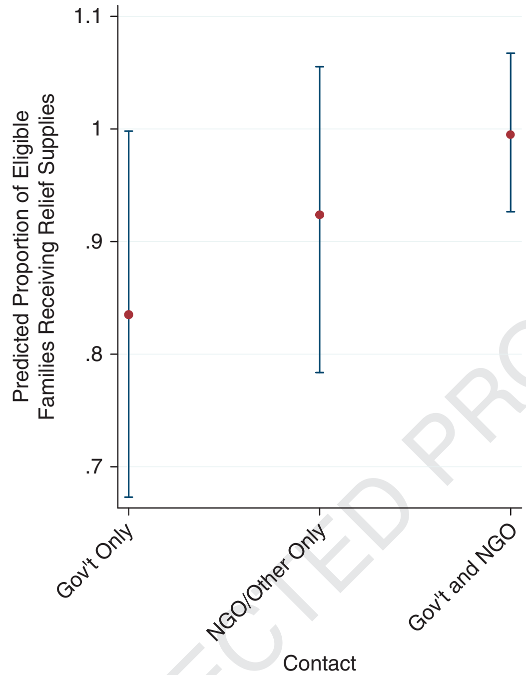
Figure 3 demonstrates that, holding all other variables at their means, villages where more families each owned a house or more than one dwelling were the most likely to receive aid. In villages where fewer than half the families owned a house, the predicted percentage of families receiving the initial relief supplies is close to 60 percent.

However, in villages where all households owned a house or more, the predicted percentage of families receiving relief supplies was 100 percent or more. That is, villages with more nuclear family structures (with fewer generations living in one house) are forecast to pull in more relief packets than extended families (with fewer houses per family, i.e., more families living under one roof).

Figure 4 holds all other variables at their means except for the group(s) in contact with the affected villages. Villages and hamlets that connected only to officials from the Government of India and local governments are labeled as "Government Only." Those that had contact only with nongovernmental organizations such as "World Vision (India), CARE (India), Catholic Relief Services (India), Project Concern International, ECHO, Oxfam, Dhan Foundation, League for Education and Development, Tamil Nadu Voluntary Health Association and Jesuits in Social Action" (UN Team for Recovery Support, 2005:5), private organizations, or other villagers are labeled Q1

FIGURE 4

In Simulations, Bridging Social Capital Has No Measurable Effect on Aid Receipt



NOTE: $N = 62$, simulations = 1,000. All other variables were held at their means. Vertical lines represent the 95 percent confidence interval around the predicted value, which is represented by the dot. Simulations were run individually with pairs of contact options to avoid the "dummy variable trap." Where confidence intervals overlap, we are unable to statistically distinguish between the variables.

as "NGO/Other Only." Finally, those organizations that were approached after the tsunami both by the Government of India and one or more NGO(s) are labeled as "Government and NGO." The dot indicates the predicted value with the edges of the line marking the 95 percent confidence intervals for the prediction.

The differences between the levels of bridging capital are quite suggestive. Villages with more extra-local contacts (i.e., hamlets that interacted with the government and at least one other organization) have higher predicted levels of aid receipt (close to 100 percent), while those who connect solely to the government have far less (close to 84 percent). However, as the 95 percent confidence intervals for these predictions overlap, we cannot reject the hypothesis that linking social capital had no effect on the predicted proportion of eligible families receiving supplies. A larger sample of villages or smaller confidence intervals may have better illuminated this factor's power. Nonetheless, based on simulations, family structure—and not linking social capital or other factors—proved most important in this policy area.

Results: Proportion of Eligible Families Receiving 4,000 Rupees

The final aid policy that I explore is the portion of eligible families receiving the 4,000 rupees. Table 4 provides the estimated coefficients for factors thought to influence what fraction of the families deemed deserving of the 4,000 rupees actually received them. First, based on the estimated coefficients, villages and hamlets in Kanyakumari and Nagapattinam were more likely to receive these 4,000 rupees than their counterparts elsewhere. Figures 5 and 6 use these data to illustrate the connections between the two most important quantities of interest: caste and wealth.

Figure 5 holds all other variables at their means and demonstrates that wealth—measured here as homes owned per capita—was an important influence on the probability of eligible families receiving 4,000 rupees in assistance. In villages where individuals owned only one-tenth of a house—meaning that there was only one home owned for every 10 people—the predicted probability of receiving this aid package was approximately 50

TABLE 4

Estimated Coefficients

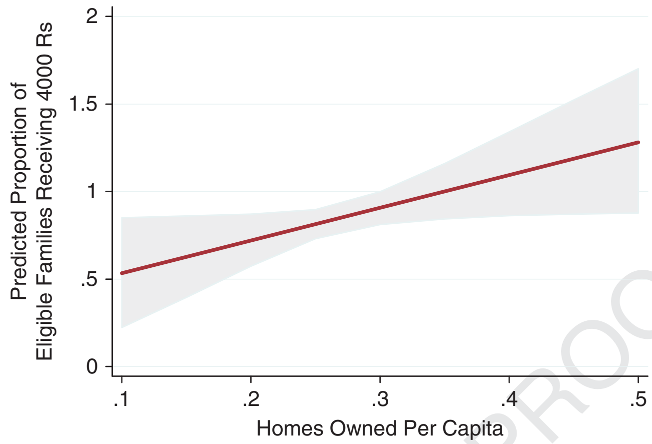
Dependent Variable: Percentage of Eligible Families Receiving 4,000 Rupees	Two-Limit Tobit
Nagapattinam District (dummy)	– 0.67
	0.45
Cuddalore District (dummy)	– 0.87*
	0.55
Thiruvallur District (dummy)	– 1.27**
	0.49
Kanyakumari District (dummy)	(omitted)
Scheduled Caste percentage	– 0.547*
	0.29
Percentage of families making 300 or fewer rupees per week	– 0.08
	0.36
Homes owned per capita	5.36**
	2.55
Constant	0.77
	0.66
/sigma	0.52
	0.13
N	43

NOTE: ***$p<0.01$; **$p<0.05$;

*$p<0.1$. Standard errors are listed beneath the estimated coefficients. Variables are omitted to avoid the "dummy variable trap," which would otherwise create perfect multicollinearity.

FIGURE 5

Wealth Influences Post-Disaster Aid Levels



NOTE: $N = 43$, simulations = 1,000. All other variables held at their mean while homes owned per capita varied. The gray outline indicates the 95 percent confidence interval around the predicted value.

percent. However, for villages where individuals had 0.5 houses per person—meaning that one home was owned for every two people—the model predicts that more than 100 percent of the registered eligible families would receive this packet.

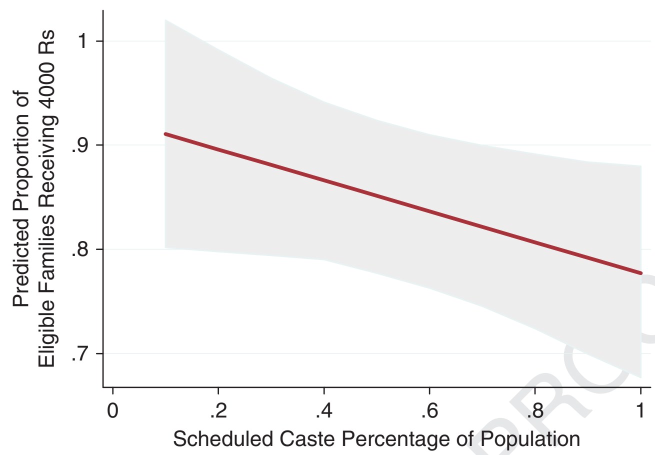
Finally, Figure 6 holds all other variables at their mean while allowing the percentage of the village who are Scheduled Caste members to vary. Here, the results indicate that hamlets and villages made up primarily of Scheduled Caste members were less likely to receive the 4,000 rupees than similar villages with fewer SC members. In a village where fewer than 20 percent of the population are Scheduled Caste members, the predicted probability of eligible families receiving the money is over 90 percent. However, in similar villages where all the members are Dalits, the chances drop below 80 percent. Caste discrimination may be taking place at the regional or administrative level as decisionmakers either deliberately or accidentally overlook villages populated primarily by Scheduled Caste families.

Discussion

Using three different types of post-tsunami aid as dependent variables, this article has explored a number of factors said to account for patterns of distribution. Although many have speculated that these marginalized inland villages received less aid overall than more visible and better organized

FIGURE 6

Scheduled Caste Percentage Suppresses the Likelihood of Assistance



NOTE: $N = 43$, simulations = 1,000. All other variables held at their means while the Scheduled Caste percentage varied. The gray outline indicates the 95 percent confidence interval around the predicted value.

coastal fishing villages, this article has used empirical evidence to show patterns of systematic exclusion based on caste. The Scheduled Caste (SC) percentage of the village proved a robust predictor of worse outcomes for individuals and families seeking to recover after the disaster. Villages with more Scheduled Caste families were most likely to spend longer times in relief camps and, more importantly, have fewer eligible individuals receiving cash assistance despite claims of objectivity and transparency. Further, pre-existing wealth was another excellent predictor of the likelihood of more assistance post-disaster. Families and individuals owning their homes were more likely to be able to attract and extract aid than those who only rented. Villages with more poorer families that rented or leased their homes were less likely to recieve the promised assistance from the government. Finally, villages and hamlets with more extended families in traditional social structure were less likely to receive help than those localities where nuclear families dominate. While model coefficients indicated a role for linking social capital, simulations and confidence intervals could not confirm these findings.

Conclusions and Avenues for Future Research

Qualitative studies of post-tsunami recovery in India underscored how Scheduled Caste hamlets such as the Dalit village of Kundrukadu often lacked the bridging social capital that could organize their relief activities and put them in contact with out-network resources (Mercks, 2007:39). Using quantitative evidence, this article has confirmed arguments about the role of caste in distribution. However, this study found only suggestive evidence that different levels of contact with extra-local institutions such as NGOs altered disbursement of aid. Although some (Mathbor, 2007) have emphasized the "public good" role that can be played by social capital in mitigating the effects of disaster, this may overlook the role of institutional discrimination in aid provision, which can swamp such social resources.

Future post-disaster distributions would do well to heed the advice of program coordinators who have suggested that relief programs begin with comprehensive profiles of affected areas. "Without this profile, the programme risks falling short of the beneficiaries' entitlements and becoming (involuntarily) discriminatory" (Brookings-Bern, 2008:11). Dalits, women, Muslims, widows, and other often marginalized groups slipped through the cracks of the process and were often provided help only after weeks or even months of waiting.

This article has demonstrated the role of caste as a cleavage point for distribution patterns. In other recent disasters around the world, ethnicity and minority status have similarly surfaced as potential predictors of worse recovery outcomes and less assistance. Discussions of post-Hurricane Katrina rebuilding in New Orleans, Louisiana have focused on race as a critical factor in distribution of aid. One study, for example, argued that necessary but often controversial post-disaster housing was sited based on patterns of race (Davis and Bali, 2008), although other research on the topic has disagreed (Aldrich and Crook, 2008) and instead focused on mobilization potential and social capital. Future research should look across disasters to test for broader patterns of racial, ethnic, or religious discrimination in post-disaster policy.

Further, this article has looked closely at the role of caste, wealth, family structure, linking social capital, and location as factors affecting how relief is distributed to the survivors of a mega-catastrophe. However, a number of scholars and practitioners have pointed out that "[d]iscrimination in relief provision—on the basis of caste, gender and economic status—must be tackled" (Banerjee and Chaudhury, 2005:43). Future work should follow up on initial studies (such as that of Enarson and Morrow (2000), Gomathy (2006), and Djupe, Sokhey, and Gilbert (2007)) to illuminate the interaction between gender, social capital, and aid distribution. Given that global warming will only increase the severity and frequency of disasters in the future, social science must work to uncover the factors that speed up (or impede) recovery following crisis.

REFERENCES

Aldrich, Daniel P., and Kevin Crook. 2008. "Strong Civil Society as a Double-Edged Sword: Siting Trailers in Post-Katrina New Orleans." *Political Research Quarterly* 61(3): 378–89.

Alexander, Rajan. 2006. *Tsunami—Build Back Better: Mantra Aside, An Aid Gone Wrong Story?* Bangalore: Development Consultancy Group.

Arvin, Mark, Anna Piretti, and Byron Lew. 2002. "Biases in the Allocation of Foreign Aid: The Case of Italy." *Review of Economic Conditions in Italy* 2:305–12.

Bakewell, Oliver. 2001. *Refugee Aid and Protection in Rural Africa: Working in Parallel or Cross-Purposes?* UNHCR Working Paper 35. London: UNHCR.

Banerjee, Paula, and Sabyasachi Basu Ray Chaudhury. 2005. *Report on a Symposium on Tsunami and the Issues of Relief, Rehabilitation and Resettlement*. Symposium held on April 23, 2005, Kolkata. Available at ⟨http://www.mcrg.ac.in/tsunami.htm⟩.

Bavinck, Maarten. 2008. "Collective Strategies and Windfall Catches: Fisher Responses to Tsunami Relief Efforts in South India." *Transforming Cultures Ejournal* 3(2): 76–92.

Bindra, Satinder. 2005. *Tsunami: 7 Hours that Shook the World*. New Delhi, India: Harper Collins.

Birner, Regina, and Heidi Wittmer. 2003. "Using Social Capital to Create Political Capital: How Do Local Communities Gain Political Influence? A Theoretical Approach and Empirical Evidence from Thailand." Pp. 291–334 in Nives Dolsak and Elinor Ostrom, eds., *The Commons in the New Millennium: Challenges and Adaptations*. Cambridge, MA: MIT Press.

Chandran, P. n.d. *Role of National Disaster Management System in the context of South Asia Tsunami 2004*. Available at ⟨http://info.worldbank.org/etools/docs/library/239529/Best%20End%20of%20Course%20Project-P%20Chandran.pdf⟩.

Davis, Belinda, and Valentina Bali. 2008. "Examining the Role of Race, NIMBY, and Local Politics in FEMA Trailer Park Placement." *Social Science Quarterly* 89(5): 1175–94.

Djupe, Paul, Anand Sokhey, and Christopher Gilbert. 2007. "Present but Not Accounted For? Gender Differences in Civic Resource Acquisition." *American Journal of Political Science* 51(4):906–20.

Dowling, J. M., and Ulrich Hiemenz. 1985. "Biases in the Allocation of Foreign Aid: Some New Evidence." *World Development* 13(4):535–41.

Enarson, Elaine, and Betty Morrow. 2000. "A Gendered Perspective: The Voices of Women." Pp. 11640. in Walter Peacock, Betty Morrow, and Hugh Gladwin, eds., *Hurricane Andrew: Ethnicity, Gender, and the Sociology of Disasters*. Miami, FL: International Hurricane Center.

Fritz Institute. 2005. *Recipient Perceptions of Aid Effectiveness: Rescue, Relief, and Rehabilitation in Tsunami Affected Indonesia, India, and Sri Lanka*. Available at ⟨http://www.fritzinstitute.org/PDFs/findings/NineMonthReport.pdf⟩.

Gill, Timothy. 2007. *Making Things Worse: How "Caste Blindness" in Indian Post-Tsunami Disaster Recovery Has Exacerbated Vulnerability and Exclusion*. Utrecht, The Netherlands: Dalit Network.

Gomathy, N. B. 2006. *The Role of Traditional Panchayats in Coastal Fishing Communities in Tamil Nadu, with Special Reference to their Role in Mediating Tsunami Relief and Rehabilitation*. Prepared for ICSF Post-Tsunami Rehab Workshop. Chennai, India: ICSF.

Human Rights Watch. 2007. *Hidden Apartheid: Caste Discrimination Against India's "Untouchables."* Available at ⟨http://www.chrgj.org/docs/IndiaCERDShadowReport.pdf⟩.

King, Gary, Robert Keohane, and Sidney Verba. 1994. *Designing Social Inquiry: Scientific Inference in Qualitative Research*. Princeton, NJ: Princeton University Press.

King, Gary, Michael Tomz, and Jason Wittenberg. 2000. "Making the Most of Statistical Analyses: Improving Interpretation and Presentation." *American Journal of Political Science* 44:341–55.

Klein, Naomi. 2007. *The Shock Doctrine: The Rise of Disaster Capitalism*. Toronto: Alfred A. Knopf.

Long, J. Scott. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: Sage Publications.

Louis, M. 2005. *Study on Discrimination and Exclusion in State Relief*. Madurai, India: People's Watch-Tamil Nadu.

Martin, Max. 2005. "A Voice for Vulnerable Groups in Tamil Nadu." *Forced Migration Review* July:44–45.

Mathbor, Golam. 2007. "Enhancement of Community Preparedness for Natural Disasters: The Role for Social Work in Building Social Capital for Sustainable Relief and Management." *International Social Work* 50(3):357–69.

Mercks, Eva. 2007. *Caste Cloud Over Tsunami Relief and Rehabilitation*. Unpublished M.A. thesis, ISHSS. Amsterdam: University of Amsterdam.

Mines, Diane. 2009. *Caste in India*. Ann Arbor, MI: Association for Asian Studies.

Nelson, Stephanie C. 2007. *Small-Scale Aid's Contribution to Long Term Tsunami Recovery*. Carolina Papers International Development 18. Chapel Hill, NC: Center for Global Initiatives. Available at ⟨http://cgi.unc.edu/research/pdf/Nelson.pdf⟩.

Praxis Institute for Participatory Practices. 2006. *Village Level People's Plans: Realities, Aspirations, Challenges*. New Delhi: Praxis Institute.

Rodriguez, Havidan, Tricia Wachtendorf, James Kendra, and Joseph Trainor. 2006. "A Snapshot of the 2004 Indian Ocean Tsunami: Societal Impacts and Consequences." *Disaster Prevention and Management* 15(1):163–77.

Rosett, Richard N., and Forrest D. Nelson. 1975. "Estimation of the Two-Limit Probit Regression Model." *Econometrica* 43(1):141–46.

Rural Education and Development Society (REDS). 2006. *Tsunami: Competition, Conflict, and Cooperation*. Tamil Nadu, India: REDS.

Salagrama, Venkatesh. 2006. *Post Tsunami Rehabilitation of Fishing Communities and Fisheries Livelihoods in Tamil Nadu, Kerala, and Andhra Pradesh*. Andhra Pradesh: Integrated Coastal Management.

SNEHA. 2006. *A Report of the Social Audit on Relief and Rehabilitation Interventions of Government of Tamil Nadu in Nagapattinam District, May 2005 to May 2006*.

Szreter, Simon. 2002. "The State of Social Capital: Bringing Back in Power, Politics, and History." *Theory and Society* 31(5):573–621.

Szreter, Simon, and Michael Woolcock. 2004. "Health by Association? Social Capital, Social Theory, and the Political Economy of Public Health." *International Journal of Epidemiology* 33(4):650–67.

Tomz, Michael, and Jason Wittenberg. 1999. "Interpreting and Presenting Statistical Results." Short course presented at the APSA Annual Meeting. Atlanta, GA.

U.N. Team for Tsunami Recovery Support. 2007. *Tsunami: India—Three Years After*. Chennai: United Nations.

Wallace, Tina. 1997. "New Development Agendas: Changes in UK NGO Policies & Procedures." *Review of African Political Economy* 24(71):35–55.

Wetterberg, Anna. 2004. *Crisis, Social Ties, and Household Welfare: Testing Social Capital Theory with Evidence from Indonesia*. Washington, DC: World Bank.

Wooldridge, Jeffrey. 2006. *Introductory Econometrics: A Modern Approach*. Mason, OH: Thomson Higher Education.

Author Query Form

Journal	SSQU
Article	736

Dear Author,

During the copy-editing of your paper, the following queries arose. Please respond to these by marking up your proofs with the necessary changes/additions. Please write your answers clearly on the query sheet if there is insufficient space on the page proofs. If returning the proof by fax do not write too close to the paper's edge. Please remember that illegible mark-ups may delay publication.

Query No.	Description	Author Response
AQ1	UN Team for Recovery Support, 2005:5 not in listed in the reference list	