ABSTRACT

Title of dissertation: RESILIENCE AND ADAPTATION TO NATURAL HAZARDS: EVIDENCE FROM INDONESIA

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The objective of this dissertation is to examine the ways in which households recover from and adapt to changing conditions as a result of natural hazards. I use Indonesia as a case study. The dissertation is divided into four chapters. In the first chapter, I give an overview on the policy relevance of studying natural disasters as well as the broad literature on the topic.

In the second chapter, I estimate the short- and medium-run economic returns to capital and inherent ability by studying the recovery of fishermen in Aceh from the 2004 Indian Ocean tsunami. Since the natural disaster wiped out a significant portion of productive physical capital among fishermen, the subsequent quasi-random infusion of aid boats generates a natural experiment. Using panel data from fishing households, I investigate whether fishermen who were relatively

more productive pre-tsunami retain their productive edge ex-post. Results suggest that (i) returns to inherent ability, measured by pre-tsunami productivity, become more important over time while returns to physical capital, measured by aid boats, become less important in the medium run, and (ii) the redistributive effects of boat aid on productivity are small and temporary.

In the third chapter, I explore the short-run (one year) behavioral changes in terms of market labor, voluntary labor, as well as borrowing through formal and informal sources among Indonesian households in the aftermath of natural hazards. I estimate the predicted number of hazards, including earthquakes, floods, landslides and storms, in each of the sampled districts in each survey year using historical data from 1980 to 2008. I then match household data with the residuals from these regressions as the unexpected number of hazards. I find that women from districts with more unexpected disasters work fewer weeks on the market. Unexpected disasters are also associated with higher probabilities of borrowing and larger loans. These results suggest that the substitution effect dominates the income effect in the short run.

In the fourth chapter, I and co-author, Philip H. Brown, investigate the link between poverty and vulnerability with respect to natural disasters by applying a utility measure of vulnerability to household panel data from Indonesia that brackets the 1997 forest fires. Using the decomposition method pioneered by Ligon and Schechter (2003), we find that households who live in areas unaffected by smoke from the fires were less vulnerable in total consumption, but they were no less vulnerable or likely to face poverty, aggregate risk, or idiosyncratic risk in food consumption than those who live in areas that were affected.

RESILIENCE AND ADAPTATION TO NATURAL HAZARDS: EVIDENCE FROM INDONESIA

by

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Dedication

To my parents.

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Chapter 1: Introduction

Humans face increasing exposure and vulnerability to natural hazards. Since 1970, there have been 3.3 million deaths due to these events, of which 95% of deaths occurred in developing countries. In addition to lives lost, disaster-related property damage equals 0.23% of total world output from 1970 to 2008 (World Bank 2011). Not only are natural hazards happening more frequently over time, in part due to climate change, but population growth and settlement in hazard-prone areas, including coastal cities and floodplains, also contribute to the rising risks from disasters.

The extensive macroeconomic literature on natural disasters focuses on the short- and long-run mean responses of annual gross domestic product (GDP) growth in every year of and after the exposure to natural hazards (see e.g. Fomby, Ikeda, and Loyaza, 2011; Loayza et al. 2012; Raddatz 2009). These studies have two common findings. First, different types of disasters have differential impacts on growth. Storms, droughts, and earthquakes are found to negatively affect GDP, while floods have a positive impact due to growth in the agricultural sector. Second, the level of economic development influences the growth impact of disasters. Growth responses from developing countries are always stronger, regardless of direction, than those from developed countries.

In contrast, the existing microeconomic literature on natural disasters is less extensive and explores a variety of outcomes. One body of work examines the short- and long-run health impacts of disasters. Maccini and Yang (2009), for instance, link adult health, education, and socioeconomic outcomes with early-life exposure to rainfall shocks in Indonesia. Aguilar and Vicarelli (2011), meanwhile, examine the impacts of ENSO events on children's health and cognitive outcomes in Mexico.

Insurance, better construction and maintenance practices, public information about floodplains and fault lines, as well as early warning systems are examples of strategies that mitigate and reduce disaster risks. However, risks cannot be completely insured or prevented by public policy. Therefore, it is important to understand how people share and cope with residual risks. From an economic perspective, it is also helpful to analyze the welfare implications of these coping mechanisms.

A substantial number of microeconomic studies explore the ways in which households, especially those in rural areas, self-insure against negative income shocks in the absence of formal insurance and credit markets. Examples of self-insurance mechanisms include savings (Paxon 1992), livestock accumulation and liquidation (Fafchamps, Udry and Czukas 1998), as well as migration and remittances (Halliday 2006). Several papers specifically investigate informal insurance networks as a form of risk sharing among affected and unaffected households at the village or community level via state-contingent transfers (see e.g. Zylberberg 2010; Czura and Klonner 2012).

The goal of this dissertation is to examine the microeconomic impacts of natural hazards and examine the ways in which households adjust their behavior to recover from and adapt to changing conditions as a result of unanticipated income shocks. I use Indonesia as a case study because of its frequent exposure to natural hazards, as well as the plausibly-exogenous variation in the exposure to hazards across geographic areas within the country.

In the second chapter, I examine the short- and medium-run economic returns to capital and inherent ability by studying the recovery of fishermen in Aceh from the 2004 Indian Ocean tsunami. Since the natural disaster wiped out a significant portion of productive physical capital among fishermen, the subsequent quasi-random infusion of aid boats generates a natural experiment. Using four waves of panel data from fishermen, I investigate whether fishermen who were relatively more productive pre-tsunami retain their productive edge ex-post, controlling for the receipt and quality of boat aid.

Focusing on the sample of fishermen who lost their pre-tsunami boats, I find that the impact of aid boat length, as a measure of boat quality, on fishing revenue is positive but diminishes over time. In contrast, I find that the impact of pre-tsunami productivity on fishing revenue increases. These results suggest that returns to inherent ability, measured by pre-tsunami productivity, become more important over time while returns to physical capital, measured by aid boats, become less important in the medium run.

In the third chapter, I explore the ways in which Indonesian households cope with natural hazards in the short run (one year) through ex-post adjustments in market labor, voluntary labor, as well as borrowing through formal and informal sources. These natural hazards include earthquakes, floods, landslides, storms and surges. In addition, I examine gender differences in the changes of these outcomes. To identify the causal impacts of these extreme weather events on household labor and borrowing, I first estimate the predicted number of hazards in each of the 216 districts in each survey year using historical data from 1980 to 2008. I then match household data with the residuals from these regressions as the unexpected number of hazards.

I find that women from districts with more unexpected disasters work fewer weeks on the market. I find no evidence of disaster-related changes in the male labor supply. Unexpected disasters are also associated with higher probabilities of borrowing and participation in rotating community credit groups, as well as larger loans. These results suggest that in the context of Indonesia, the substitution effect dominates the income effect in the short run.

In the fourth chapter, I investigate the link between poverty and vulnerability with respect to natural disasters by applying a utility measure of vulnerability to panel data that brackets a major forest fire. This chapter is a paper that I co-author with Philip H. Brown, titled "Natural Disasters and Vulnerability: Evidence from the 1997 Forest Fires in Indonesia," which appears in Volume 11, Issue 1 of the B.E. Journal of Economic Analysis & Policy in October, 2011. We estimate and analyze household vulnerability in both total consumption and food consumption. We find that households with a high degree of exposure to smoke from the fires were more vulnerable in total consumption but no more vulnerable in food consumption.

Chapter 2: Returns to Capital and Ability: A Natural Experiment in Aceh

2.1 Introduction

There is a growing interest among economists in estimating returns to capital in small-scale productive activities in developing countries (see Banerjee and Duflo 2005, for a review). The empirical strategy relies on exogenous variation in capital, which is usually attained through randomized control trials in which additions in capital are generated at random. These studies find positive effects of capital shock on firm-level growth, suggesting that firms were credit-constrained. However, credit constraint is not the sole determinant of firm-level growth as there is evidence of heterogeneous returns to capital among firms. Udry and Anagol (2006), for example, find heterogeneous returns by crop type in a sample of small-scale agricultural producers in Ghana.[1] de Mel, McKenzie and Woodruff (2008) also find significantly larger treatment impacts for Sri Lankan enterprises owned by males and no positive return in enterprises owned by females. In addition, Fafchamps et al. (2014) find heterogeneous effects between cash and in-kind treatments among microenterprises

[1]Among farmers growing traditional crops, the returns are found to be 50% per year. Among those producing pineapples on plots of similar sizes, the returns are 250% per year.

in Ghana. While the impact of cash is lower in male-owned businesses, only in-kind grants cause growth among those that are female-owned. This result contrasts with predictions of the Ramsey model of investment in which profit-maximizing firms grow after removing credit constraints regardless of the form of credit provided.

The existing literature suggest various explanations for the differential levels of and returns to capital investments. Fafchamps et al. (2014), for example, suggest the lack of self-control as a plausible explanation for the "flypaper" effect. Comparing the relative performance of individual Norwegian sealing vessels between seasons, Salvanes and Steen (1994) show that "fishing luck" or a stochastic element is an important determinant of fishing performance in terms of efficiency scores based on a revenue model. Among producers in the garment industry in India, Banerjee and Munshi (2004) argue that given differential productivity levels, differences in the strength and type of social ties among two social groups lead to differences in access to capital that in turn explain the different levels of investments between them. Alternatively, Dodlova (2015) show that risk, in addition to credit constraint, is a determinant of returns to capital among Peruvian microenterprises.

This chapter aims to contribute to the above literature by using micro-level data to examine the economic returns to capital in the short- and medium-run using a natural experiment in Indonesia. Specifically, I study the recovery of fishermen in Aceh from the 2004 Indian Ocean tsunami. I also investigate how the changes in returns to capital compare with the changes in the returns to inherent fisherman ability. Since the natural disaster wiped out a significant portion of productive capital among fishermen, the subsequent quasi-random distribution of aid boats generates a natural experiment. Using panel data from fishing households who are surveyed six months after the tsunami, and subsequently in 2007, 2009, and 2012,[2] I investigate whether fishermen who were relatively more productive pre-tsunami retain their productive edge ex-post, controlling for the receipt and quality of boat aid.

This research question relates to studies that explore the possibility of catching up among units with low initial levels of productivity. Janes (2013), for example, uses experimental evidence from Sri Lanka to examine whether one-time capital grants enable microenterprises to reach the productivity levels of small- and medium- sized enterprises (SMEs). The study finds that capital grants lead to gains in productivity only among firms with owners who have higher cognitive ability and are more risk averse. In addition, these gains are sufficient to generate convergence in productivity between microenterprises and SMEs, but not with large businesses. In this chapter, I similarly examine whether boat aid generates productivity gains that are sufficient for fishermen with low levels of productivity pre-tsunami to catch up with fishermen who were more productive.

More generally, this study contributes to the literature that examine the short- and long-term adjustments to environmental hazards. From a macroeconomic perspective, Hornbeck (2012) finds that after the American Dust Bowl in the 1930s that led to permanent soil erosion in many counties on the American plains, agricultural adjustments, including land-use adjustments, recovered less than 25% of the initial

[2] I gratefully acknowledge the support of the National Science Foundation (SES 0416840) and the National Institute of Health (R01 HD057188) on a project managed by J. Vernon Henderson.

agricultural costs. The main form of economic adjustment is population declines in the more-eroded counties. From a microeconomic perspective, Manabu (2013) uses the same context in Indonesia as this chapter to characterize the post-tsunami occupational choice among fishermen. Using the total catch in 2007 as a measure of average fishing productivity, the author finds that the combination of low quality boat aid and the expansion of alternative sectors drove many pre-tsunami fishermen to choose non-fishing jobs, resulting in a smaller and less productive fishing sector. Instead of examining the fishing sector as a whole, I focus on the economic performance of individual fishermen who stay fishing post-tsunami, controlling for the quality of boat aid.

Aid boats provided by donors are on average seven meters long, with a market resale price of 15,500,000 Rupiah (about USD$1,550).[3] Thus, the per-meter value of a boat is approximately 2,214,286 Rupiah or USD$221. Given the median weekly income for fishing households is 375,000 Rupiah (about USD$38), these aid boats represent not only productive capital but also asset due to its nontrivial market value (Nose 2014). In terms of quality, anecdotal evidence suggests that aid boats are inadequate in terms of material (unseasoned wood or plastic), design (too lightweight to withstand waves in the Indian Ocean), and durability due to the lack of equipment and experience of boat builders (Thorburn 2009). In terms of assignment, the supply of boats at the village level is based on the adoption decisions of NGOs (Henderson and Lee 2014). Overall, Masyrafah and McKeon (2008) conclude that the allocation

[3] The annual exchange rate in 2005 is 9,852.62 Rp/$1USD; the exchange rate in 2007 is 9392.17 Rp/$1USD; the 2009 exchange rate is 9527.25 Rp/$1USD, and the 2012 exchange rate is 9631.27 Rp/$1USD.

of aid from both local and international NGOs is inefficient due to the myriad of objectives and targets. For example, some subdistricts (*kecamatans*) were adopted by multiple donors, resulting in an excess supply of aid boats.

Focusing on fishermen who lost their pre-tsunami boats, I find that the transfer of capital increases overall productivity, as the returns to aid boat length in terms of fishing revenue are positive. However, I find that the returns to aid boat length diminish over time, suggesting that boat aid helps restore the pre-disaster equilibrium but the redistributive effects on productivity are small and temporary. In contrast, I find that returns to pre-tsunami productivity are positive and increase over time, suggesting that fishermen who were relatively more productive pre-tsunami continue to be productive ex-post. My results suggest that returns to inherent ability, measured by pre-tsunami productivity, are more important than returns to physical capital in the long run.

This result is consistent with work done by de Mel, McKenzie and Woodruff (2008) showing heterogenous returns with respect to entrepreneurial ability but not with measures of risk aversion or uncertainty among microenterprises in Sri Lanka. More broadly, it contributes to a growing literature that suggests existing firm-level conditions may lead to systematic differences in rates of return (e.g. Siba 2015, McKenzie and Woodruff 2006, McKenzie and Woodruff 2008).[4] Moreover, this result nuances the finding in Bigsten et al. (2000), who show higher returns to physical capital than human capital among small and medium scale manufacturing firms in

[4]McKenzie and Woodruff (2006, 2008) conduct experiments among small, urban micro enterprises in Mexico and find rates of return that range from 40% to 360% per year.

Africa. Instead of comparing the returns to fishing ability and boats in absolute terms, I show their relative importance as determinants of fishing performance over time.

This result also contributes to the literature that studies the long-term economic impact of aid in developing countries. The established empirical evidence on this topic is mixed. Evaluating the impact of a large-scale, rural development program in China that includes infrastructure investments, improved social services and individual loans, Chen, Mu and Ravillion (2004) find that a decade after the start of the program, the long-term average impact on income and consumption is zero, despite evidence that short-term income gains are sizable and mostly saved. In contrast, de Mel et al. (2012) find that one-time business grants to microenterprises in Sri Lanka not only have short-term effects, but also non-zero impacts in the long run. The authors find a 10 percentage point higher rate of survival among microenterprises five years after the grant, as well as higher monthly profits for male-owned businesses. The result that a one-time infusion of capital has long-term economic impact is suggestive of the existence of initial poverty traps or under-investment due to productive nonconvexities. The infused capital may have enabled owners to conduct lumpy investments with high returns that sustain over time.

Consistent with the finding in de Mel et al. (2012), I find that the impact of aid boats on the economic performance of fishermen in Aceh is positive and non-zero in 2012, seven years after the tsunami hit. In addition, this chapter contributes to the discussion by showing that the impact of one-time capital infusion is non-stationary at different points in time, suggesting that the one-time grant of aid boats may have functioned as an emergency insurance for fishermen who lost their pre-tsunami boats so that they can stay fishing before the credit markets are able to recover from the aggregate shock.

By estimating the returns to physical capital that is distributed through an aid program in post-tsunami Aceh, this study is also related to the literature that evaluates the efficacy of in-kind transfers (see e.g. Currie and Gahvari 2008, Jacoby 1997). Controlling for the plausibly exogenous assignment of boat aid with respect to pre-tsunami fishing productivity, I find that the receipt of aid boat increases the probability of fishing post-tsunami. This result suggests that boat aid is useful in sustaining household participation in fishing. However, I find that the effect of aid boat length - a measure of productive capacity - on the probability of fishing is not statistically different from zero. This result highlights the importance of boat aid itself, regardless of its quality, on household participation in fishing.

The rest of the chapter is organized as follows: Section 2.2 describes the data. Section 2.3 presents the empirical strategy and robustness checks on the data. Section 2.4 discusses the estimation results. Section 2.5 concludes.

2.2 Data

2.2.1 Description

The data used in this chapter come from a large field study in Aceh, Indonesia, that includes surveys at the village and fisherman head levels.[5] The project covers

[5] The title of the project is "Population and Economic Recovery in Coastal Aceh: Aid and Village Institutions" (principal investigator, J. Vernon Henderson, Brown University/National Bureau of

the universe of fishing villages in two tsunami-affected *kabupatens*: Banda Aceh and Aceh Besar.[6] The universe of fishing villages is defined as having a significant pre-tsunami fishing presence as certified by *Panglima Laot*, a fishermen community organization in Aceh. The target population is fishing households living in these coastal villages that were most heavily damaged by the 2004 Indian Ocean tsunami. Thus, the survey is not representative of the general population in Aceh (Nose 2014). Rather, the sample of fishermen represents the average fisherman in the province.[7] Figure 2.1 shows the geographic coverage of the project.

The baseline survey was conducted in June and July of 2005, covering 544 pre-tsunami fishing households in 111 fishing villages. All of these villages around Banda Aceh were hit by the tsunami. The survey represents 25% of all pre-tsunami boat owners and 45% of surviving boat owners in these villages. The sampling frame was drawn from a list of former fishing boat owners assembled by *Panglima Laot*, which worked on rebuilding the fishing communities with disaster relief agencies. In each village, fishing households were proportionally sampled from the list. Retrospective information on pre-tsunami household characteristics, boat measures and fishing activity was collected.

In terms of lives lost, less than 50% of the population survived (Freire, Henderson and Kuncoro 2011). About 9% of houses and 6% of public buildings in the

Economic Research). This study is funded by the National Science Foundation (SES 0416840) and the National Institute of Health (R01 HD057188).

[6]Provinces in Indonesia are divided into districts (*kabupaten*), which are further divided into subdistricts (*kecamatan*).

[7]Nose (2014) compares and finds that the average household characteristics of fishermen in this survey are similar to those of fishermen from the 2004 SUSENAS sample. The SUSENAS is a series of large-scale multi-purpose socioeconomic surveys that covers a nationally representative sample typically composed of 200,000 households.

overall sample survived. In terms of productive capital for fishermen, the survival rate of boats was under 6%. Although differentials in income levels exist among fishing households pre-tsunami, the devastating impact of the tsunami leveled the field for all fishing households.

The second round of the household survey was conducted in 2007, when the original fishermen from the baseline survey had relocated away from refugee camps to permanent homes. The 2007 survey recovers two-thirds of these original fishermen because some of them cannot be found. In addition, some of the fishermen from the baseline survey are dropped from the 2007 and later surveys because their status as pre-tsunami boat owners in the baseline was erroneous. I compare the averages of pre-tsunami characteristics for each group and check whether the differences are statistically significant. Table 2.16 in Appendix B reports these differences. Fishermen who remained after the baseline are only different from those who attrited in terms of having fewer household members and being more likely to have fathers who were also fishermen (significant at the 1% and 5% levels). Thus, there is little evidence from the data to suggest that the fishermen who attrited from the sample after the baseline are systematically different from those who remain in the sample post-tsunami.[8]

In addition, 443 new fishing households were added to the sample in 2007. Many of these new fishing households became boat owners through the aid process after the tsunami. The third and fourth rounds of the survey are conducted in 2009

[8]As a robustness check, I account for the presence and absence of fishing households in each post-tsunami survey round using a probit model and inverse probability weights (Wooldridge 2007) (see Section 2.3.4 below).

and 2012, resurveying 353 and 330 of the original households covered in the baseline survey.[9] To examine whether more productive fishermen pre-tsunami retain their productive edge among their peers ex-post, I restrict my estimation sample to include only panel fishing households who have been present since the 2005 baseline survey. This sample construction process results in an unbalanced panel of 1,590 observations and a balanced panel of 1,243 observations (approximately 350 households) over four survey years (2005, 2007, 2009 and 2012).

2.2.2 Summary Statistics

2.2.2.1 Household Characteristics

Table 2.1 presents the summary statistics of household demographics. The average household has four members, with 1.6 members as income earners. Based on the average weekly income, I classify 23.2% of households as poor, with earnings less than 250,000 Rupiah (about USD$25) per week; 43.3% as low income, with between 250,000 Rupiah and 500,000 Rupiah (about USD$50) weekly earnings; 23.2% as middle income, with between 500,000 Rupiah and one million Rupiah (about USD$100) weekly earnings, and 10.1% of households as high income, with more than one million Rupiah in earnings per week. Approximately 30% of households have debts to repay, and the most prevalent form of savings is in cash, followed by gold or jewelry, financial institutions such as commercial banks, and lastly with family members.

[9] It is important to note that the survey team aims to recover as many of the baseline fishermen as possible without a differential preference over those who have received boat aid.

Over 97% of households have male households heads, who are 40 years old on average. Fewer than 5% of household heads have no formal education, about 50% have attended elementary schools, 20% and 15% have attended junior and senior high schools, and only 2% to 3% have attended college or university across the survey years. In terms of social integration, approximately 25% of spouses of household heads attend *arisan* meetings, a form of community-level rotating credit organization in Indonesia, and over 50% of household heads attend the fishermen head meetings.

2.2.2.2 Fishing in Aceh

In Aceh, the traditional fishermen association, *Panglima Laot*, regulates the fishing industry. For example, the association certifies who may be boat captains and settles disputes. In a typical fishing operation, if a fisherman is a boat captain but not a boat owner, it is likely that the captain has to split the revenue from catch with the boat owner (Garces et al. 2006). The profit-sharing rule varies by region. Generally, the boat owner takes 50% to 60% of the profit, of which he gives a 5% to 7% cut to the captain, who also gets the biggest share of the remaining 40% to 50% of the profit set aside for crew members (Janssen 2005).

Since the baseline survey in 2005 draws its sample from a list of boat owners, 100% of baseline households in my estimation sample own boats, with 79.7% of them being boat captains as well. As the 2004 tsunami wiped out 94% of pre-tsunami fishing boats, both boat ownership and captain status have declined in subsequent survey years. In 2007, 61.8% of households own boats, with 49.2% being captains as well; in 2009, boat ownership has increased, with 70.5% of households being owners on average, and 43.9% are boat captains. In 2012, boat ownership declines slightly to return to 2007 levels, with 63.9% of households owning boats and 43% of households being boat captains. In my estimation sample, less than 10% of households own more than one boat. Thus, I only use information on the main fishing boat, including its characteristics and catch, in the empirical analyses.

The post-tsunami surveys ask about four types of catch - tuna, small fish, mollusks and crustaceans - from a typical fishing trip during the week preceding the survey. However, the large variance in the reported catch for each type of fish across the survey years suggests that estimates of average catch are likely to have substantial measurement errors. Thus, I use the reported monetary amounts received for catch as measures of productivity rather than the reported catch. Since this financial information is unavailable pre-tsunami, I predict fishing revenue using reported catch (see equation (2.3) below).

2.2.2.3 Fishing Boat

Table 2.3 presents the average characteristics of each boat type owned by sampled households. Across all survey rounds, 49.2% of households own a $thep-thep$, which is among the smallest of boat types in terms of weight, length, as well as engine power. On average, all boats owned are approximately seven to eight meters long, with engine power between 22.3 to 31.7 horsepower. Boats weigh 2.2 metric tons on average pre-tsunami, 2.4 metric tons in 2007, 3.9 metric tons in 2009 and 3.8 metric tons in 2012. The increase in boat weight over time suggests that fishing households may have upgraded their boats as they recover from loss of fishing productivity in the aftermath of the 2004 tsunami.

Indeed, Figure 2.2 shows that the distribution of fishing boats owned by the surveyed fishermen are not constant over time. Although over 50% of fishermen in all survey years own the smallest boats, such as *thep-thep* and *temple*, the percentage of fishermen owning these small boats is the lowest in 2012. This reduction in small-boat owners is accompanied by higher percentages of medium-boat owners (*darat* and *pancing*) and big-boat owners (*labi-labi* and *langgar*).

To more precisely examine the change in boat types for each fisherman, I present in Table 2.4 the transition matrices of the types of boat in use in each post-tsunami survey year with respect to the pre-tsunami boat type. In each of the matrixes, the post-tsunami boat types are ordered from small to large from left to right and the pre-tsunami boat types go from small to large from top to bottom. Thus, the numbers on the diagonal represent the percentages of sampled fishermen who use the same type of boat post- and pre-tsunami; the numbers below the diagonal reflect down-sizing and those above the diagonal reflect size upgrades.

Overall, there is evidence of downsizing for the majority of fishermen and only low incidences of upgrade. In 2007, 46.86% of fishermen are using boats that are smaller than the pre-tsunami boats. Only 5.57% of fishermen have upgraded their boats. Specifically, 45.9% of pre-tsunami large boat (*labi-labi* and *langgar*) owners own the smaller *thep-thep* or *temple*, with only 32.8% of them retaining a big boat.

By 2012, however, only 28.79% of pre-tsunami large boat owners still own smaller boats and nearly half of them have upgraded to the pre-tsunami boat types. In fact, 12.73% of fishermen own boats in 2012 that are bigger than the pre-tsunami boats.

I find similar trends of recovering pre-tsunami boat types among fishermen who own small and medium boats but at a lower rate. Among pre-tsunami medium-boat owners, for instance, only 10.2% use the same boat types in 2007 and 23.4% do in 2012. These trends suggest that fishermen who own bigger boats pre-tsunami have the highest rates of recovering pre-tsunami boat types, due to possible reasons such as higher productivity or better access to capital. I formally test for the recovery of pre-tsunami productive capacity in Section 2.4.2 below.

2.2.2.4 Boat Aid

In terms of boat aid, Table 2.2 shows that 63.9% of households in 2007 report having received an aid boat, which is 3.4 meters long on average. Some households applied for an aid boat but have not received one by the time of the 2007 survey. Thus, 44.7% of households have received their first aid boat between 2007 and 2009. The majority (37.1%) of aid boats distributed are $thep-thep$s, followed by 26.88% being *temple*s and 24.19% being other types. Table 2.5 shows that fishermen who have lost their pre-tsunami boats as well as those with surviving boats applied for boat aid. In fact, a higher percentage of pre-tsunami boat survivors applied for boat aid than that of fishermen who lost their boats.

An important feature of this aid program is that the transfer of aid appears to be unconditional on aid application. Panel B of Table 2.5 shows that among fishermen who have lost their boats, over 90% received aid boats, regardless of aid application. In contrast, application does seem to matter for the granting of aid among those with surviving boats. As the third panel shows, 85.3% of those who have applied for boat aid receive the transfer while only 56.7% of those who did not apply receive the transfer. I formally test for the exogeneity of boat aid with respect to aid application in Section 2.3.3 below.

In terms of aid boat usage, among fishermen with surviving boats, 1.89% of them use the aid boat received as the main fishing boat in 2007 and 5.26% of them do so in 2009. Among fishermen who lost their pre-tsunami boats, 14.29% use the aid boat as the main fishing boat in 2007 and 8.52% of them do so in 2009. All of the fishing boats in use in 2012 have replaced earlier aid boats. This is consistent with the termination of boat aid after 2009 and the fact that the lifespan of aid boats are generally shorter than five years. In my empirical analyses, I focus on the sample of fishermen who lost their pre-tsunami boats.

2.3 Empirical Strategy

My empirical work is motivated by an infinite-time horizon investment model with a one-time transfer of capital stock (see Appendix A). I make the following assumptions. First, fishermen are endowed with heterogeneous fishing ability. Second, fishing ability complements physical capital, which is the fishing boat, implying that fishermen have different optimal boat sizes and types. Third, I assume the presence of a functioning boat market.[10] Hence, boats are not sticky and fishermen have no reason to keep the wrong types of boat. This assumption is consistent with the data used in this study: among fishermen who lost their pre-tsunami boats, only 14.29% use the aid boat as the main fishing boat in 2007 and 8.52% of them do so in 2009.

2.3.1 Main Equations

In this chapter, I examine whether fishermen who were more productive pre-tsunami retain their productive edge ex-post, controlling for the receipt and quality of boat aid. To do so, I estimate two main models. First, I investigate whether the post-tsunami productive capacity, which is measured by boat length, is influenced by pre-tsunami productivity and/or boat aid by running the following regression:

$$\begin{aligned} Length_{i,k,m,t} = \zeta_0 + \zeta_1 Productivity_{i,2004} + \zeta_2 Aid_i + \zeta_3 AidLength_i \\ + \tau_t (Productivity_{i,2004} * y_t) + \varphi_t (AidLength_i * y_t) \\ + \upsilon_k + \omega_t + \epsilon_m + \nu_1 \end{aligned} \tag{2.1}$$

where *Length* is the length of the current boat in use at time t (where t = 2007, 2009, 2012). $Productivity_{i,2004}$ is the level of productivity for fisherman i pre-tsunami. *Aid* is a dummy variable that equals 1 if a household has received a fishing boat on aid in the period after the baseline survey in 2005 and before the conclusion of the 2009 survey. *AidLength* is the length of the aid boat received in meters.

To allow for the possibility that the effect of pre-tsunami productivity is dif-

[10] I argue that the boat market in Aceh is not a market of lemons because there is no asymmetry of information regarding the quality of boats (Akerlof 1970). If a fisherman owns a bad boat or the wrong type of boat, he will be able to sell it for the market price.

ferent from year to year, I interact $Productivity_{i,2004}$ with year dummies, y_t. Hence, ζ_1 represents the effect of pre-tsunami productivity on boat length in 2007, $\zeta_1+\tau_{2009}$ represents the effect in 2009; and $\zeta_1+\tau_{2012}$ represents the effect in 2012. I test the hypothesis that the effect of pre-tsunami productivity changes over time against the null that the effect is identical in each year, i.e. $\zeta_1=\zeta_1+\tau_{2009}=\zeta_1+\tau_{2012}$. Similarly, I allow the effect of aid boat length on current boat length to be different across years by interacting $AidLength_i$ with the year dummies. Overall, $\zeta_1+\tau_t$ represents the impact of pre-tsunami productivity on current capital and $\zeta_3+\varphi_t$ represents the impact of aid capital on current capital. Finally, I include year fixed effects, ω_t; interview month fixed effects, ϵ_m; and subdistrict fixed effects, υ_k.

Second, I wish to examine whether post-tsunami fishing income is impacted by pre-tsunami productivity and/or boat aid. Thus, I run the following regression:

$$\begin{aligned} ln(R_{i,k,m,t}) = {} & \zeta'_0+\zeta'_1 Productivity_{i,2004}+\zeta'_2 Aid_i+\zeta'_3 Length_{i,t} \\ & +\tau'_t(Productivity_{i,2004}*y'_t)+\varphi'_t(Length_{i,t}*y'_t) \\ & +\upsilon'_k+\omega'_t+\epsilon'_m+\nu_2 \end{aligned} \tag{2.2}$$

where R is the reported revenue from catch, including tuna, small fish, mollusks, and crustaceans, during the last regular fishing trip a week prior to the interview. To control for within-fisherman correlation, I cluster the standard errors at the fisherman level when estimating equations (2.1) and (2.2).

2.3.2 Estimation Approach

The estimation of equations (2.1) and (2.2) is complicated by two factors. The first is how to measure pre-tsunami productivity. In this chapter, I propose two alternative measures. First, I use the reported length of the pre-tsunami boat as a proxy. The limitation of using pre-tsunami boat length is that it is an indirect measure, as boat length is likely a function of not only productivity, but also access to capital. The advantage of boat length is that it is measured exactly. The second measure of productivity is similar to the measure of efficiency in Krishnan, Nandy and Puri (2014). Specifically, I estimate a log-linear Cobb-Douglas production function for each fisherman, region and month:

$$\begin{aligned} ln(R_{i,k,m}) = \sigma_0 + \sigma_1 Type_i + \sigma_2 ln(Length_i) + \sigma_3 ln(Hours_i) \\ + \sigma_4 ln(Length_i * Hours_i) + a_k + b_m + \nu_3 \end{aligned} \tag{2.3}$$

where R is the imputed revenue from reported catch during an average pre-tsunami trip. $Type$ is a vector of pre-tsunami boat type dummies. $Length$ is boat length in meters, a measure of productive capacity. $Hours$ represents the number of fishing hours of the average trip, a proxy for the inputs used in the production process. I also include an interaction term between boat length and hours to allow for differential effects of fishing hours on productivity across different boat lengths. It is easy to show that fisherman-level productivity is the residuals from equation (2.3), as they represent the portions of revenue that cannot be explained by observed boat or fisherman characteristics alone.

Since fishing revenue is only reported post-tsunami, I predict pre-tsunami revenue using reported catch pre-tsunami and the relative prices derived from the relationship between catch and revenue post-tsunami. Although fishing and market conditions have likely changed after the tsunami, causing the coefficients that relate catch to revenue to be different before and after, I argue that this approach is reasonable because the relative prices of different types of fish have not changed. According to the Agency for Reconstruction of Aceh (*Badan Rehabilitasi dan Rekonstruksi*), there has been a decline in the supply of fresh fish as well as a decline in demand due to the loss of purchasing power. Consequently, fresh fish prices have remained stable compared to pre-tsunami levels, with a small increase in line with the general price inflation (FAO/WFP 2005). On the whole, the relative prices of the different species of fish have remained unchanged.

The second complication with estimating equation (2.2) is that the length of the current boat and pre-tsunami productivity can be endogenous if there are unobserved fisherman characteristics that affect both. For example, a highly-motivated fisherman might have both a high level of pre-tsunami productivity and a bigger fishing boat. To produce unbiased estimates of equation (2.2), I employ a two-stage least squares approach with aid boat length as the identifying instrument for current boat length. The first stage is estimated as follows:

$$\begin{aligned} Length_{i,k,m,t} = \phi_0 + \phi_1 Productivity_{i,2004} + \phi_2 Aid_i + \phi_3 AidLength_i \\ + \eta_t (Productivity_{i,2004} * j_t) + \pi_k + \varnothing_t + \varsigma_m + \nu_4 \end{aligned} \tag{2.4}$$

and the second stage is as follows:

$$
\begin{aligned}
ln(R_{i,k,m,t}) = {} & \phi_0' + \phi_1' Productivity_{i,2004} + \phi_2' Aid_i + \phi_3' Len\hat{g}th_{i,k,m,t} \\
& + \eta_t'(Productivity_{i,2004} * j_t') + \rho_t(Len\hat{g}th_{i,k,m,t} * j_t') \\
& + \pi_k' + \o_t' + \varsigma_m' + \nu_5
\end{aligned}
\tag{2.5}
$$

where $Len\hat{g}th$ is the predicted length of the current boat from equation (2.4).

For the length of the aid boat to be a valid instrument, the assignment and quality of aid boat should be uncorrelated with pre-tsunami productivity and fisherman characteristics. If the fishermen who receive aid boats are systematically different from those who did not, an OLS regression of the impact of aid boat on fishing productivity will produce biased estimates. Likewise, if fishermen who receive better quality aid boats were more productive pre-tsunami, the estimated effect of the quality of aid boats on post-tsunami productivity is biased because the quality of aid boat is correlated with unobserved fisherman ability.

2.3.3 Assignment of Boat Aid

To determine whether the assignment of aid boats is plausibly exogenous with respect to pre-tsunami productivity and fisherman characteristics, I first divide the sample into fishing households that have lost their pre-tsunami boats (80% of the sample) and those with surviving boats (20% of the sample). Table 2.6 compares the means of various pre-tsunami characteristics across the two sub-samples. I find that fishermen who have lost their boats and those with surviving boats are not statistically different in terms of their production gear, fishing habits and household characteristics pre-tsunami. There are differences in other respects, but they are generally statistically marginal. Specifically, fishermen with surviving boats are more likely to be indebted, have fewer income earners in the household, are more likely to fish near shore and less likely to do so within the lagoon (significant at the 10% level). A regression explaining boat survival confirms that pre-tsunami characteristics including these factors do not predict boat survival but *kecamatan* dummies do. This result suggests that boat survival is purely due to the pre-tsunami geographical location of the fishermen.

Table 2.7 shows, however, that in the post-tsunami years 2007, 2009 and 2012, the average boat characteristics across the sub-samples are statistically different from one another. Although the sample of fishermen with lost boats are given longer aid boats in 2007 or 2009, their current boat lengths are shorter than fishermen with surviving boats (significant at the 1% levels). Unsurprisingly, I find that fishermen with surviving boats report slightly higher fishing revenue than those with lost boats (significant at the 10% level). These comparisons show that the fishermen who did and who did not lose their boats are not identical, suggesting that they should be treated separately in subsequent analyses.

To check that the assignment of boat aid is plausibly exogenous, I estimate the following probit model separately for each sub-sample:

$$P(Aid_{i,k} = 1) = F(\psi_0 + \psi_1 Productivity_i + \psi_2 Apply_i + \psi_3 Debt_i + \psi_4 H_i + d_k) \quad (2.6)$$

where all variables are at the fishing household level and all independent variables are at the pre-tsunami levels. *Productivity* is the measure of productivity using the residuals from the estimation of imputed revenue in equation (2.3). In an alternative specification, the pre-tsunami boat length in meters is used in place of *Productivity* as a direct measure of productive capacity. *Apply* is a dummy variable that equals 1 if the household has submitted an application for boat aid post-tsunami. *Debt* is a dummy variable that equals 1 if the household has outstanding loans. H is a vector of variables depicting household head characteristics, including his age, education, and whether his father was a fishermen. The test of exogeneity is to reject the null hypothesis that at least one of the coefficients is not zero. A particular concern over the exogeneity of boat aid is that its assignment can be explained by pre-tsunami productivity. Thus, I test the hypothesis that $\psi_1 = 0$ against the null that pre-tsunami productivity predicts aid boat assignment.

To check that more productive fishermen pre-tsunami were not given bigger aid boats, I estimate the following regression:

$$AidLength_{i,k} = \psi_0' + \psi_1' Productivity_i + \psi_2' Apply_i + \psi_3' Debt_i + \psi_4' H_i + d_k' + \nu_6 \quad (2.7)$$

Columns (1) to (4) of Table 2.8 show that among fishermen who lost their boats, the assignment and quality of boat aid, measured by length, are uncorrelated with both measures of pre-tsunami productivity (residuals from equation (2.3) and boat length), as well as pre-tsunami household characteristics and aid application. In addition to evaluating the predictive powers of each individual variable, I also test that groups of variables may be jointly significant predictors of aid boat assignment. Specifically, I examine the joint significance of groups of variables that depict the education levels of the household head and other household characteristics. The F-statistics are displayed in the table. In these tests, I fail to reject the null hypotheses that the coefficients on these variables are jointly zero.

Columns (5) to (8) show that among fishermen with surviving boats, those who have submitted an application for boat aid are more likely to receive an aid boat (significant at the 1% level) and to receive bigger aid boats (significant at the 5% level). This result suggests any analysis on the sample of fishermen with surviving boats should account for the selection into aid application. One way to do so is to estimate a probit model on the relevant fishermen to explain boat aid application:

$$P(Apply_{i,k} = 1) = G(\xi_0 + \xi_1 Owner_i + \xi_2 Length_i + \xi_3 Debt_i + \xi_4 H_i + s_k) \qquad (2.8)$$

where *Apply* is a dummy that equals 1 if fisherman i has submitted an application for boat aid post-tsunami. I then use equation (2.8) to form inverse probability weights and use them to control for selection into aid application (Wooldridge 2007).

Overall, as shown in Table 2.8, I find that the assignment of boat aid is unrelated to levels of pre-tsunami productivity. The only statistically significant predictors of the assignment of boat aid in both sub-samples are the *kecamatan* dummies. This result implies that certain *kecamatan* qualities may have led to its adoption by a certain NGO, resulting in a particular kind of aid delivery. Thus, in my analysis of the impact of boat aid on productivity, I include *kecamatan* fixed effects.

2.3.4 Selection into the Sample

For robustness, I check the probability of selection into the survey and into fishing in each post-tsunami survey round. I assume that selection into the initial survey is exogenous and I am only concerned about selection into (i.e. attrition out of) subsequent survey years.[11] I estimate the probit model:

$$P(sample_{i,k,t} = 1) = \Phi(\delta_0 + \delta_1 Aid_i + \delta_2 AidLength_i + \delta_3 Owner_{i,t} + \delta_4 X_{i,t} + \alpha_k + \gamma_t) \tag{2.9}$$

where *sample* is a dummy variable that equals 1 if fishing household i from *kecamatan* k at time t (where t = 2007, 2009, 2012) is present in each post-tsunami survey year. *Owner* is a dummy variable that equals 1 if at least one household member is a boat owner. X is a vector of variables depicting characteristics of the household head, including his age, education, and whether his father was a fishermen. α_k is a set of *kecamatan* dummies that control for *kecamatan*-specific qualities, including distance from the capital of the province, Banda Aceh, which has the the highest NGO presence, and others that are otherwise unobserved in the data. γ_t represents year fixed effects.

Specification (1) in Table 2.9 shows evidence of selection on observables. Among the statistically significant predictors of whether a household is present in each post-

[11] The 2007 survey recovers two-thirds of the fishing households that were surveyed in the 2005 baseline survey. If reasons for households to be lost in 2007 are correlated with outcome variables of interest in this study, estimates will be biased.

tsunami survey round, the impact of receiving an aid boat is the strongest. A pre-tsunami fishing household who has received an aid boat is more likely to be present in the sample by 8.6 percentage points (significant at the 1% level). However, only the receipt of aid boat matters while the value of the boat as a productive asset, as measured by length, does not predict attrition from the sample.

Boat ownership decreases the probability of presence in the sample by 7.03 percentage points (significant at the 1% level) while attendance of *arisan* meetings or fishermen head meetings, which are proxies for the extent of social integration at the household level, has no such predictive power. This result suggests that attrition may be a result of relocation and households who own boats are more able to move. A limitation of these data is that this hypothesis cannot be tested empirically.

Pre-tsunami income levels also affect the probability of presence in the post-tsunami sample. In particular, compared with high-income households - those with average weekly income of more than one million Rupiah (about USD$100) - poor households with average weekly income of less than 250,000 Rupiah (about USD$25) pre-tsunami are less likely to attrite from the sample by 4.1 percentage points (significant at the 10% level). Similarly, low income households with between 250,000 and 500,000 Rupiah (about USD$25 to $50) in average weekly income have a 5.3 percentage points lower probability to attrite (significant at the 5% level). These results suggest that households with higher income pre-tsunami have more options to relocate post-tsunami and are less likely to stay in the sample. This interpretation is consistent with the estimated impact of boat ownership discussed above.

2.3.5 Selection into Fishing

While the baseline survey is drawn from a universe of pre-tsunami fishing households, not all of the original households keep fishing in subsequent years. In principle, one keeps fishing if profits or income from fishing are greater than those from alternate occupations. Since I do not observe income from alternate sources among fishermen, I estimate the probability of fishing using the probit model:

$$P(fish_{i,k,t,m} = 1) = \Phi'(\delta'_0 + \delta'_1 Aid_i + \delta'_2 AidLength_i + \delta'_3 Length_{i,2004} + \delta'_4 X_{i,t} + \alpha'_k + \gamma'_t + \mu_m) \tag{2.10}$$

where $fish_i$ is a dummy variable that equals 1 if household i has at least one member that reports fishing as his primary activity. $Length_{i,2004}$ is the length of the pre-tsunami fishing boat. μ_m is a set of interview month dummies that capture the seasonality of fishing and other occupations in Aceh. The regressors in equation (2.10) capture the determinants of income from fishing and other types of work.

Column (2) in Table 2.9 shows results from equation (2.10) while column (3) shows results of the same model estimated with inverse probability weights that account for selection bias into the sample (see Section 2.3.4). The signs and magnitudes of the explanatory variables are similar across specifications with and without weights, suggesting that the size of the selection bias is small.

I find that the receipt of boat aid not only explains presence in the sample, but it is also a strong predictor of whether a household participates in fishing in each post-tsunami survey round. Results from the model with inverse probability weights that control for sample selection show that a household that receives an aid boat are more likely to continue fishing post-tsunami by 24.6 percentage points (significant at the 5% level). Since the survival rate of boats post-tsunami is under 6% (Henderson and Lee 2014), the positive impact of boat aid on the probability of post-tsunami fishing suggests that boat aid is useful in sustaining household participation in fishing. The statistically insignificant effect of the length of aid boats highlights the importance of boat aid itself, regardless of its quality, on sustaining household participation in fishing.

In addition, pre-tsunami income levels are important predictors of whether a household continues to fish or not post-tsunami. While poor and low-income households are more likely to stay in the sample compared with high-income households, they are less likely to continue fishing. Poor households are less likely to fish by 22.3 percentage points (significant at the 5% level) in the weighted model, while low-income households are less likely to fish by 15.6 percentage points (significant at the 10% level) and mid-income households do so by 19.2 percentage points (significant at the 5% level). This result suggests that households who are poorer pre-tsunami may have quit fishing to look for occupations with higher returns post-tsunami. Overall, the magnitude of the impact of pre-tsunami income levels is comparable but smaller than that of boat aid, suggesting that both boat aid and pre-tsunami household income are strong determinants of post-tsunami participation in fishing.

2.4 Results

2.4.1 Post-Tsunami Performance

The main goal of this chapter is to estimate the returns to capital and ability in the short- and medium-run by studying the post-tsunami performance among fishermen who lost their pre-tsunami boats. In Table 2.10, columns (1) and (2) display results of equation (2.1) in which I use post-tsunami boat length as a measure of productive capacity. Using the residuals from equation (2.3) as measures of pre-tsunami productivity in column (1), I find that its impact on current boat length is statistically insignificant except in 2012, when a 10% increase in the unpredicted fishing revenue pre-tsunami, as a measure of inherent fishing ability or productivity, increases the current boat length post-tsunami by 1.65 meters (significant at the 5% level).[12]

Using pre-tsunami boat length as an alternative proxy for pre-tsunami performance in column (2), I find that the impact of pre-tsunami boat length on current boat length is positive and statistically significant, with the biggest impact in 2012. For each additional meter of the pre-tsunami boat, the current boat length is 0.174 to 0.258 meter longer in the post-tsunami years (significant at the 5% levels). Thus, the impact of pre-tsunami productivity or inherent ability on post-tsunami productive capacity increases over time.

[12] In Table 2.10, column (1), the effect of pre-tsunami productivity in 2007 is the coefficient -0.0925. The effect in 2009 is the sum of the coefficients -0.0925 and 0.0951. Similarly, the effect in 2012 is the sum of -0.0925 and 0.257, which equals 0.1645. The interpretation of the impacts of pre-tsunami boat length, aid boat length, and instrumented current boat length in Tables 2.10 to 2.13 follows the same logic.

The impact of aid boat length on current boat length is also positive and statistically significant (at the 1% level) across both specifications. However, the impact peaks in 2009 and becomes smaller by 2012. In column (1), for instance, the negative coefficient of -4.967 on the aid boat dummy shows that among fishermen who lost their pre-tsunami boats, those who have an aid boat end up having smaller boats than those who did not receive aid. Taking the ratio of this coefficient on that of the aid boat length, I find that only receiving an aid boat that is at least 7.19 meters has a positive effect on current boat length in 2007 (statistically significant at the 1% level). By 2012, only fishermen who receive an aid boat of at least 10.52 meters has a positive effect on current boat length (statistically significant at the 1% level). An F statistic of 5.85 allows us to reject the null hypothesis that the impact of aid boat length is equal in each post-tsunami year (significant at the 10% level). The magnitude and sign of the coefficients remain consistent in column (2). Thus, I conclude that the impact of aid boat length on post-tsunami productive capacity diminishes over time.

Column (3) shows results of estimating equation (2.2), which uses fishing revenue as the measure of post-tsunami performance. Consistent with the impact on post-tsunami boat length, I find that pre-tsunami productivity has an increasing and positive effect on fishing income. In 2007, fishermen with a 10% higher pre-tsunami productivity has 0.83% lower fishing income but 0.5% higher income in 2012. In terms of aid boat, I also find consistent evidence that its returns on fishing revenue diminishes over time. Specifically, the impact peaks in 2009, when receiving an aid boat of 6.53 meters or longer leads to higher fishing revenue than otherwise (significant at the 1% level).

Columns (4) and (5) show the two-stage least squares results from equations (2.4) and (2.5). Column (4) presents the first-stage estimation, in which aid boat length is a strong and positive predictor of current boat length, with a chi-squared statistic of 70.27 (significant at the 1% level). Column (5) shows the second-stage result that the impact of instrumented current boat length on fishing revenue also diminishes over time, with its peak in 2009. An additional 10 meters in current boat length is associated with 2.7% more in fishing revenue in 2009 and 2.06% more in 2012. Overall, I fail to reject that the returns to aid boat length in terms of current length in each post-tsunami year are statistically identical. However, the finding that returns to innate fisherman ability, as reflected by pre-tsunami productivity, are the highest in 2012 and that the returns to aid boat are the lowest suggest that the redistributive effects of boat aid are small and temporary.

As a robustness check, I estimate the main equations (2.1) and (2.2) with three sets of inverse probability weights to account for different possible types of selection bias. Table 2.11 shows estimation results with weights that control for selection into the full sample; Table 2.12 presents results that incorporate weights to control for selection into fishing; Table 2.13 shows weighted results that control for selection into application for boat aid. In all three exercises, I find consistent results with the unweighted analysis in Table 2.10, suggesting that my main results are robust to specifications that account for possible selection biases.

A second robustness check is provided in Table 2.17 of Appendix B, which repeats the analysis in Table 2.10 using a pooled sample that includes fishermen with surviving boats. I allow for different sets of coefficients for fishermen with and without surviving boats and test for their equality. Statistical tests show that I cannot reject that all of the coefficients are equal across the two sub-samples. Thus, in Table 2.18, I repeat the analysis in Table 2.17 but impose the same set of coefficients on the two groups of fishermen because the former sub-sample consists of fewer observations and may result in the lack of statistical power. Overall, results from the pooled sample are consistent with that shown in Table 2.10.

Another robustness check confirms that the estimation of pre-tsunami productivity is not sensitive to the assumption of the Cobb-Douglas functional form. Specifically, I estimate a translog production function with boat length and fishing hours as the two inputs in the production of fishing and take the residuals as measures of pre-tsunami productivity. I obtain estimates that are similar to those from equation (2.3). Table 2.19 repeats the main estimations (2.1) and (2.2) with the use of pre-tsunami productivity derived from the translog function. The estimated coefficients of the residuals are consistent in their signs and magnitude with those of the residuals from equation (2.3).[13]

A related robustness check ensures that results from the main equations (2.1) and (2.2) are robust to the use of pre-tsunami productivity as a proxy for fishermen's innate ability. Specifically, I estimate a log-linear Cobb-Douglas production function for each fisherman, region and month with the log of pre-tsunami fishing revenue per meter of the pre-tsunami boat as the dependent variable. Thus, the resulting

[13]Coefficients of the residuals from the translog production function are no more or less than 15% different from those of residuals from the Cobb-Douglas production function.

residuals measure fisherman-level productivity per meter of the fishing boat. Table 2.20 presents the estimation of equations (2.1) and (2.2) with the use of per-unit pre-tsunami productivity. The estimated coefficients of the residuals are consistent in their signs and magnitude with those of the residuals from equation (2.3).[14]

A final robustness check ensures that the estimation results of the main equations (2.1) and (2.2) are unbiased by observations from *kecamatan*s where 100% of fishermen who lost their pre-tsunami boats receive aid boats, regardless of aid application.[15] Specifically, Table 2.21 repeats the analysis of Table 2.10 by restricting the sample to fishermen from kecamatans with less than 100% delivery of aid boats. The signs and magnitudes of coefficients from this restricted sample are consistent with those from the full estimation sample. Thus, including fishermen from *kecamatan*s where all fishermen with lost boats receive a replacement does not bias the main results.

2.4.2 Long-Term Impact of Boat Aid

In this chapter, I also wish to examine whether fishermen are able to upgrade and/or return to their pre-tsunami productive capacity. Hence, I run the following regression to estimate the determinants of the latest available post-tsunami boat length:

[14] Coefficients of the per-unit residuals are no more or less than 15% different from those presented in Table 2.10.

[15] Of the ten *kecamatan*s surveyed, three of them have 100% aid boat delivery among fishermen who lost their pre-tsunami boats. These *kecamantan*s are *Lhok Nga*, *Leupung*, and *Jaya*.

$$
\begin{aligned}
Length_{i,k,t} = \kappa_0 + \kappa_1 Length_{i,2004} + \kappa_2 AidLength_i + \kappa_3 Age_{i,t} \\
+ \kappa_4 Age_{i,t}^2 + \kappa_5 Father_i + c_k + \nu_7
\end{aligned}
\tag{2.11}
$$

where t is the last survey year when information on the length of the boat is available for fisherman i. Age is the age of fisherman i at time t; and $Father$ is a dummy that equals 1 if his father was also a fisherman. I wish to test the following hypotheses: (i) $\kappa_1 = 1$, (ii) $\kappa_2 = 0$, and (iii) κ_1 is statistically different from κ_2.

Table 2.14 presents the results of estimating equation (2.11). Among fishermen with lost boats, 19.92% of current boats are received with aid, suggesting that aid boats do not stick. Moreover, I find that pre-tsunami boat length is a strong predictor of current boat length. Column (1) shows that for each additional meter of the pre-tsunami boat, the current boat is 0.27 meters longer while the equivalent impact of aid boat is 0.17 meter (significant at the 5% level). As column (2) shows, I find consistent results after controlling for fisherman characteristics. In both specifications, I can strongly reject that pre-tsunami boat length has a one-to-one relationship with current boat length (significant at the 1% level). I also reject that aid boat length has no impact on current boat length (significant at the 5% level). Overall, I cannot reject that the impacts of aid boat and pre-tsunami boat lengths on current boat length are identical.

Among fishermen with surviving boats, only 6.45% of the boats currently in use are still the aid boats.[16] I also find evidence that the pre-tsunami boat length

[16] Table 2.8 shows that aid application matters for the receipt and quality of aid only among

is a stronger predictor of current boat length than aid boat length. Specifically, for each additional meter of the pre-tsunami boat, the current boat is 0.66 meter longer (significant at the 1% level). However, the impact of aid boat length on current boat length is statistically insignificant. Similar to the sub-sample of fishermen who lost their pre-tsunami boats, I can strongly reject that pre-tsunami boat length has a one-to-one relationship with current boat length among fishermen with surviving boats (significant at the 5% level). However, in contrast to columns (1) and (2), I cannot reject that aid boat length has no impact on current boat length. Therefore, I can conclude that the impacts of aid boat and pre-tsunami boat lengths on current boat length are statistically different (significant at the 1% level).

Overall, the consistent finding in both groups of fishermen that pre-tsunami boat length is a statistically significant and positive predictor of the post-tsunami equivalent suggests that controlling for the in-kind transfer of boats, functioning markets allow fishermen to recover their pre-tsunami productive capacity, which I measure with boat length. Testing the equality of the coefficients on aid boat length from columns (1) and (3), i.e. comparing 0.171 with 0.0875, the t-statistic is 0.698. The equivalent test on the coefficients from columns (2) and (4), i.e. comparing 0.170 with 0.0224, generates a t-statistic of 1.475. In both cases, I fail to reject the null that the estimated impact of aid boat length on current boat length is identical across the two sub-samples.

To check that these results are robust and not driven by the current boat

fishermen with surviving boats. Thus, I only include inverse probability weights from equation (2.8) in Table 2.14 to control for selection into aid application for the sub-sample of fishermen with surviving boats.

being the aid boat itself, I restrict the sample to fishermen who no longer use the aid boat. Table 2.15 shows the estimation results. I find that the signs of coefficients are consistent with those in Table 2.14. However, coefficients on the pre-tsunami boat length are larger in magnitude. Among fishermen who lost their pre-tsunami boats, for instance, each additional meter of the pre-tsunami boat is associated with an additional 0.36 meter in current boat length while the equivalent impact of aid boat is 0.16 meter (significant at the 1% and 5% levels). However, I cannot reject the null that the impacts of pre-tsunami and aid boat lengths are identical. Testing the equality of the coefficients on aid boat length from columns (1) and (3), i.e. comparing 0.157 with 0.0963, the t-statistic is 0.458. The equivalent test on the coefficients from columns (2) and (4), i.e. comparing 0.155 with 0.0231, generates a t-statistic of 1.256. Therefore, in both cases, I fail to reject the null that the estimated impact of aid boat length on current boat length is identical across the two sub-samples.

2.5 Conclusions

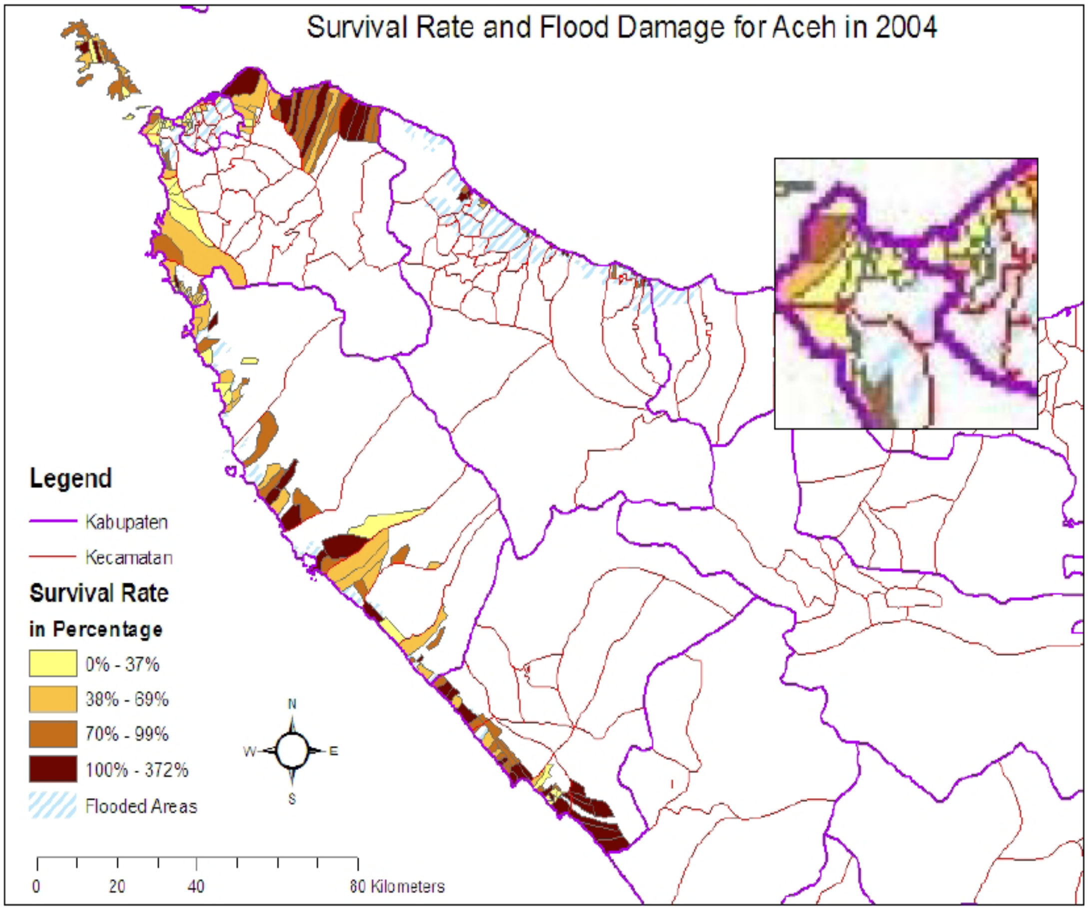
In this chapter, I use a unique setting in which a natural disaster removed existing differentials in capital stock, which is then quasi-randomly reassigned through an aid program, to estimate the returns to capital and inherent ability in the short- and medium-run. Using data on Indonesian fishermen who were severely affected by the 2004 Indian Ocean Tsunami, I find that boat aid increases overall productivity as the returns to aid boat length in terms of post-tsunami boat length and fishing revenue are positive. However, these returns diminish over time. The returns to pre-tsunami productivity are also positive, suggesting that fishermen who were more productive pre-tsunami retain their productive edge ex-post. Moreover, these returns increase over time. Thus, I conclude that returns to inherent ability are more important than returns to capital in the long run. In addition, boat aid helps restore the pre-disaster equilibrium but the redistributive effects on productivity are small and temporary.

The finding of this study has important policy implications. In particular, I find that the receipt of boat aid increases the probability of household participation in fishing post-tsunami. Given that the tsunami has a devastating impact on the fishing industry ex-post, in addition to the expansion of the construction sector, this result suggests that in-kind transfer of the essential productive capital (in this case, a fishing boat) may be used as an effective policy instrument to retain participation in the industry that has suffered the most direct blow from a natural disaster.

Second, the results in this chapter imply the existence of markets for aid boats such that aid boats are either directly useful or can be sold for their value. In particular, I show that the length of the latest post-tsunami boat is positively and more strongly correlated with the pre-tsunami boat length than the aid boat length. This result suggests that fishermen are able to sell their aid boats in exchange for boats that are similar to their pre-tsunami types. Since boat length is an important determinant of productivity, this finding suggests that fishermen tend to go back to their pre-tsunami productive equilibrium.

If the objective of the capital transfer was to restore the pre-disaster equilibrium, then the result of this chapter points to a successful aid program. However, these results also suggest that returns to inherent fishing ability are more important than returns to the infusion of capital in the long run. That is, more productive fishermen pre-tsunami end up retaining their productive edge ex-post, despite the quality of aid boat received. Hence, investments in human capital rather than a simple infusion of physical capital may be more effective in reducing the productivity gap among fishermen in Aceh.

Figure 2.1: Map of Survey Area



Source: Henderson and Lee (2014)

Figure 2.2: Distribution of Fishing Boats by Collapsed Types

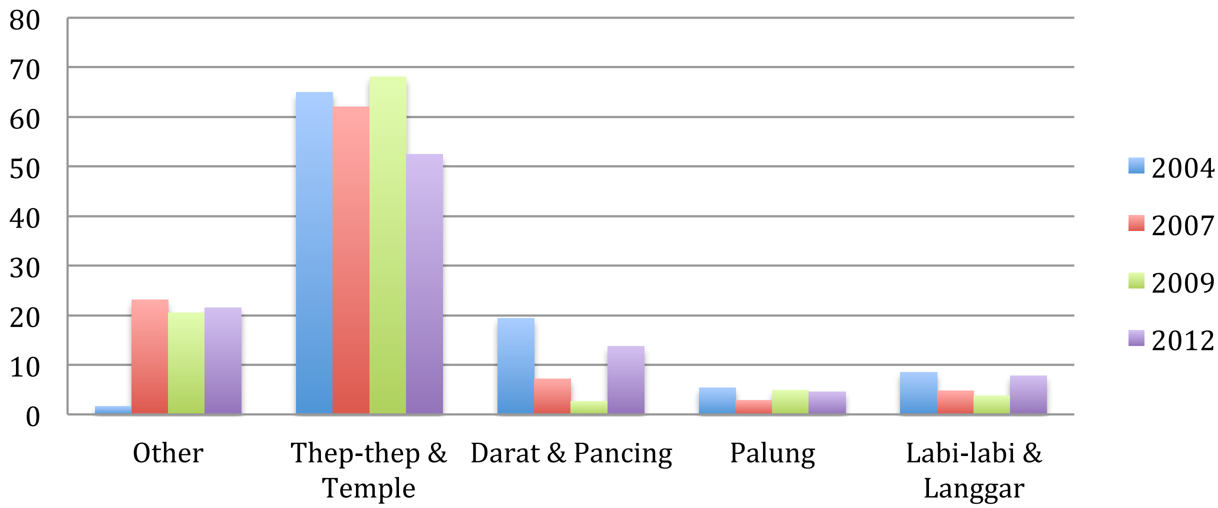


Table 2.1: Summary Statistics - Household Characteristics

	2005		2007		2009		2012	
VARIABLES	mean	standard deviation	mean	standard deviation	mean	standard deviation	mean	standard deviation
Household characteristics								
Household size	4.967	1.834	3.942	1.792	4.102	1.686	4.206	1.703
Currently fishing	1.000	0.000	0.618	0.487	0.705	0.457	0.639	0.481
Boat owner	1.000	0.000	0.492	0.501	0.439	0.497	0.430	0.496
Boat captain	0.797	0.402	0.442	0.497	0.411	0.493	0.376	0.485
Owns debt	0.308	0.462	0.286	0.452	0.317	0.466	0.210	0.408
Savings in gold	N/A	N/A	0.121	0.326	0.184	0.388	0.149	0.357
Savings in Cash	N/A	N/A	0.179	0.384	0.283	0.451	0.231	0.422
Savings in banks	0.241	0.428	0.081	0.273	0.133	0.340	0.112	0.316
Savings with family members	0.480	0.500	0.025	0.156	0.011	0.106	0.024	0.154
Household head characteristics								
Male	0.994	0.074	0.992	0.091	0.975	0.158	0.970	0.172
Age	41.453	9.898	42.476	10.915	43.206	11.160	46.228	11.028
Father was a fisherman	0.040	0.197	0.086	0.280	0.116	0.321	0.112	0.316
No school	0.070	0.255	0.044	0.206	0.041	0.199	0.014	0.116
Elementary school	0.518	0.500	0.509	0.501	0.484	0.500	0.546	0.499
Junior high school	0.242	0.429	0.237	0.426	0.248	0.432	0.227	0.420
Senior high school	0.166	0.372	0.162	0.369	0.181	0.386	0.155	0.362
Vocational school	0.011	0.105	0.008	0.091	0.003	0.053	0.006	0.078
College or university	0.018	0.135	0.025	0.156	0.037	0.189	0.033	0.180
Wife attends arisan meetings	0.234	0.424	0.214	0.411	0.318	0.467	0.262	0.440
Attends fishermen head meetings	0.619	0.486	0.571	0.496	0.501	0.501	0.355	0.479
Trauma after 2004 tsunami	N/A	N/A	0.372	0.484	0.195	0.397	0.339	0.474
New wife after tusnami	N/A	N/A	0.406	0.492	0.398	0.490	0.381	0.487
Observations	**543**		**364**		**353**		**330**	

Table 2.2: Summary Statistics - Boat Characteristics and Fishing Activity

	2005		2007		2009		2012	
VARIABLES	mean	standard deviation	mean	standard deviation	mean	standard deviation	mean	standard deviation
Boat characteristics								
Age	3.775	3.430	2.123	1.783	N/A	N/A	N/A	N/A
Length (meters)	8.856	3.925	7.711	3.237	7.624	3.018	8.080	3.777
Weight (metric tons)	2.234	3.744	2.377	9.230	3.944	5.170	3.796	8.238
Engine capacity (HP/PK)	31.722	69.865	26.763	26.386	22.305	16.048	31.251	40.610
Number of boats	1.037	0.216	0.685	0.499	0.668	0.501	0.697	0.487
Cold box	0.713	0.453	N/A	N/A	0.538	0.500	0.767	0.423
GPS	N/A	N/A	N/A	N/A	0.055	0.228	0.098	0.298
Fishing activity								
Near shore fishing	0.029	0.169	0.170	0.376	0.232	0.423	0.127	0.334
Within lagoon fishing	0.295	0.456	0.212	0.409	0.224	0.417	0.142	0.350
Outside lagoon fishing	0.595	0.491	0.118	0.323	0.178	0.383	0.418	0.494
Deep sea fishing	0.081	0.273	0.014	0.117	0.011	0.106	0.015	0.122
Hours fishing last trip	16.494	28.022	11.147	17.070	16.780	33.312	13.249	17.477
Number of crew members	3.557	4.505	N/A	N/A	2.718	4.085	3.155	3.571
Operating cost last trip*	N/A	N/A	N/A	N/A	481,269	1,046,785	501,379	1,211,762
Tuna (pieces)	23.208	45.906	120.431	188.315	45.005	124.815	229.689	495.452
Small fish (kg)	36.806	153.846	40.494	55.268	48.472	257.649	144.017	678.939
Mollusks (kg)	65.140	136.917	14.889	10.365	2.500	1.118	25.273	42.420
Crustaceans (kg)	14.274	21.605	9.743	8.667	5.333	2.563	0	N/A
Total amount received for catch	N/A	N/A	752,799	1,825,145	1,315,199	6,095,684	908,666	2,115,973
Aid boat								
Received boat on aid	N/A	N/A	0.639	0.481	0.447	0.498	N/A	N/A
Sold/abandon boat on aid	N/A	N/A	0.028	0.165	0.390	0.489	N/A	N/A
Length of aid boat	N/A	N/A	3.442	4.213	3.301	4.164	N/A	N/A
Observations	**543**		**364**		**353**		**330**	

Note: *Monetary values are reported in nominal Indonesian Rupiah.

Table 2.3: Boat Characteristics by Type

	Boat Type							
VARIABLES	Darat	Thep-thep	Labi-labi	Langgar	Palung	Pancing	Temple	Other
Boat characteristics (mean)								
Age	4.344	2.919	3.500	6.072	6.000	3.538	2.261	2.967
Length (meters)	8.216	7.480	13.063	19.056	9.231	9.620	7.454	5.783
Weight (GT)	2.669	2.520	3.786	13.681	3.551	2.326	2.854	3.599
Engine capacity (HP/PK)	24.778	20.938	58.818	116.810	37.769	33.591	30.556	14.736
Cold box	0.515	0.690	0.938	0.926	0.625	0.745	0.786	0.451
GPS	0.000	0.017	0.333	0.611	0.000	0.600	0.000	0.013
Percentage owned by fishing households	3.21	49.22	1.39	5.56	4.69	10.24	13.37	12.33
Percentage distributed as aid boat	0.54	37.10	0.54	4.84	2.69	3.23	26.88	24.19

Table 2.4: Transition Matrixes of Boat Types

	2007 boat types					
2004 boat types	Other	Thep-thep & Temple	Darat & Pancing	Palung	Labi-labi & Langgar	Total
Other						
Thep-thep & Temple	0.2695	0.6484	0.0568	0	0.0253	1
Darat & Pancing	0.2653	0.5969	0.102	0	0.0357	1
Palung	0.1509	0.4151	0	0.434	0	1
Labi-labi & Langgar	0.0328	0.459	0.1803	0	0.3279	1
Total	0.242	0.6051	0.0739	0.0293	0.0497	1

Note: % with the same type of boat = 47.27%; % upgraded = 5.57%; % downgraded = 46.86%.

	2009 boat types					
2004 boat types	Other	Thep-thep & Temple	Darat & Pancing	Palung	Labi-labi & Langgar	Total
Other	0	1	0	0	0	1
Thep-thep & Temple	0.22	0.7378	0.0156	0.0178	0.0089	1
Darat & Pancing	0.2431	0.6464	0.0663	0.0221	0.0221	1
Palung	0.1176	0.2353	0	0.6471	0	1
Labi-labi & Langgar	0.087	0.5217	0	0	0.3913	1
Total	0.2112	0.6783	0.0266	0.0476	0.0364	1

Note: % with the same type of boat = 53.63%; % upgraded = 4.32%; % downgraded = 42.06%.

	2012 boat types					
2004 boat types	Other	Thep-thep & Temple	Darat & Pancing	Palung	Labi-labi & Langgar	Total
Other	1	0	0	0	0	
Thep-thep & Temple	0.2876	0.5226	0.109	0.0226	0.0583	1
Darat & Pancing	0.0935	0.6355	0.2336	0.0187	0.0187	1
Palung	0	0.4	0	0.6	0	1
Labi-labi & Langgar	0.1212	0.2879	0.1212	0	0.4697	1
Total	0.2161	0.5245	0.1355	0.0467	0.0771	1

Note: % with the same type of boat = 45.16%; % upgraded = 12.73%; % downgraded = 42.11%.

Table 2.5: Pre-Tsunami Boat Survival, Aid Boat Application and Grant

Panel A: Boat Survival and Aid Boat Application

	Aid Application		
Pre-Tsunami Boat Survival	Yes	No	Total
Yes	51.95%	48.05%	77
No	45.89%	54.11%	401
Total	224	254	478

Panel B: Aid Boat Application andGrant Among Fishermen who Lost Boats

	Aid Boat Received		
Aid Application	Yes	No	Total
Yes	91.27%	8.73%	126
No	92.09%	7.91%	139
Total	243	22	265

Panel C: Aid Boat Application and Grant Among Fishermen with Surviving Boats

	Aid Boat Received		
Aid Application	Yes	No	Total
Yes	85.29%	14.71%	34
No	56.67%	43.33%	30
Total	46	18	64

Table 2.6: Descriptive Statistics: Pre-Tsunami Characteristics

	(1)	(2)	(3)
VARIABLES	A: Sample (survived boats)	B: Sample (lost boats)	A-B
Pre-tsunami:			
Productivity (residuals)	0.0702	0.0385	0.0317
	(0.216)	(0.153)	(0.126)
Boat length	9.0588	8.612	0.447
	(0.562)	(0.305)	(0.620)
Indebted	0.491	0.355	0.135*
	(0.0707)	(0.0389)	(0.0787)
Age	41.56	40.967	0.593
	(1.288)	(0.915)	(1.651)
Household size	5.039	5.197	-0.158
	(0.274)	(0.146)	(0.299)
No school	0.12	0.0656	0.0544
	(0.0464)	(0.0225)	(0.0460)
Elementary	0.62	0.582	0.0380
	(0.0693)	(0.0448)	(0.0829)
Junior high school	0.140	0.230	-0.0895
	(0.0496)	(0.0382)	(0.0677)
Senior high school or above	0.12	0.123	-0.00295
	(0.0464)	(0.0299)	(0.0553)
Father was a fisherman	0.06	0.0492	0.0108
	(0.0339)	(0.0197)	(0.0376)
Wife attends *arisan* meetings	0.275	0.289	-0.0150
	(0.0631)	(0.0369)	(0.0735)
Number of income earners	1.353	1.684	-0.331*
	(0.111)	(0.0931)	(0.173)
Fishing near shore	0.0588	0.0132	0.0457*
	(0.0333)	(0.00927)	(0.0250)
Fishing within lagoon	0.236	0.362	-0.127*
	(0.0600)	(00391)	(0.0759)
Fishing outside lagoon	0.588	0.553	0.0356
	(0.0696)	(0.0405)	(0.0807)
Fishing at deep sea	0.118	0.0723	0.0453
	(0.0456)	(0.0211)	(0.0449)
Fishing hours	21.255	16.856	4.400
	(5.539)	(2.415)	(5.257)
Number of crew	3.824	3.358	0.466
	(0.718)	(0.342)	(0.718)

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.7: Descriptive Statistics: Post-Tsunami Characteristics

	(1)	(2)	(3)
VARIABLES	A: Sample (survived boats)	B: Sample (lost boats)	A-B
Post-tsunami:			
Fishing revenue	1,646,548	1,203,797	442,750.8*
	(295,849.7)	(88,078.78)	(229,932)
Boat length	8.639	7.391	1.247***
	(0.344)	(0.121)	(0.296)
Aid boat length	5.597	6.722	-1.126***
	(0.452)	(0.131)	(0.350)
Household size	3.829	4.008	-0.179
	(0.125)	(0.0712)	(0.157)
Fishing near shore	0.230	0.240	-0.00967
	(0.0343)	(0.0172)	(0.0386)
Fishing within lagoon	0.368	0.364	0.00449
	(0.0393)	(0.0193)	(0.0436)
Fishing outside lagoon	0.329	0.290	0.0391
	(0.0382)	(0.0182)	(0.0414)
Fishing at deep sea	0.0197	0.0129	0.00685
	(0.0113)	(0.00453)	(0.0107)
Fishing hours	14.462	11.493	2.969*
	(1.867)	(0.754)	(1.766)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Assignment of Boat Aid

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Sample (lost boats)				Sample (survived boats)			
	aid (dummy)		aid boat length		aid (dummy)		aid boat length	
Applied for boat aid	0.0706	0.0705*	0.702	0.914	0.365***	0.367***	2.407	3.616**
	(0.0388)	(0.0334)	(0.583)	(0.650)	(0.0924)	(0.0682)	(1.294)	(1.002)
Pre-tsunami productivity (residuals)	-0.00939		-0.360		-0.00554		-1.247	
	(0.0290)		(0.433)		(0.0915)		(0.929)	
Pre-tsunami boat length		7.24e-06		0.147*		0.000537		0.242
		(0.00985)		(0.0755)		(0.0136)		(0.133)
Indebted	-0.0370	-0.0384	-1.161	-0.738	-0.124	-0.115	-2.511	-0.878
	(0.0759)	(0.0748)	(1.671)	(1.286)	(0.217)	(0.138)	(2.258)	(1.642)
Age	-0.0145	-0.00886	0.106	0.237	-0.133***	-0.136*	0.240	-0.558
	(0.0214)	(0.0182)	(0.130)	(0.239)	(0.0269)	(0.0638)	(0.805)	(1.070)
Age squared	0.000156	9.44e-05	-0.00114	-0.00267	0.00155***	0.00160*	-0.00218	0.00769
	(0.000235)	(0.000216)	(0.00165)	(0.00282)	(0.000351)	(0.000762)	(0.00997)	(0.0136)
i: Elementary	0.247	0.237	3.033*	3.283	-0.0873	-0.0846	-1.181	-0.535
	(0.187)	(0.185)	(1.581)	(1.877)	(0.0604)	(0.0803)	(1.843)	(1.698)
ii: Junior high school	0.247	0.241	3.775*	3.777*	-0.314	-0.321	-0.443	-1.788
	(0.165)	(0.179)	(1.713)	(1.940)	(0.234)	(0.271)	(3.044)	(2.803)
iii: Senior high school or above	0.247	0.247	1.351	1.589	-0.459	-0.455	-3.111	-2.918
	(0.192)	(0.186)	(1.979)	(1.936)	(0.379)	(0.378)	(4.613)	(4.087)
a: Father was a fisherman	0.0415	0.0420	-0.862	-0.446	-0.0161	-0.0302	2.205	-0.179
	(0.169)	(0.174)	(1.638)	(1.350)	(0.188)	(0.179)	(4.031)	(5.118)
b: Wife attends *arisan* meetings	-0.00704	-0.0133	1.087	0.726	0.0370	0.0350	0.854	-0.0298
	(0.0829)	(0.0718)	(1.699)	(1.375)	(0.191)	(0.201)	(2.286)	(1.661)
Constant	0.805	0.702	-0.627	-4.193	3.277***	3.332**	-2.445	10.67
	(0.528)	(0.421)	(2.894)	(5.427)	(0.675)	(1.349)	(15.31)	(20.11)
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistcs of testing:								
(education vars) i=ii=iii=0	0.76	0.67	2.15	1.78	1.50	2.02	0.44	0.26
(household head vars) a=b=0	0.29	0.13	0.26	0.20	0.04	0.03	0.24	0.00
Observations	108	112	107	111	48	48	45	45
R-squared	0.217	0.217	0.259	0.260	0.392	0.392	0.455	0.430

Note: Robust standard errors in parentheses. Standard errors are clustered at thesub-district (kecamantan) level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9: Probit Model of Selection into Sample and Fishing

	(1)	(2)	(3)
VARIABLES	presence in sample	household fishing	
			weighted
Boat aid (dummy)	0.0865***	0.232**	0.246**
	(0.0208)	(0.101)	(0.102)
Aid boat length	0.000796	0.00490	0.00312
	(0.00290)	(0.0126)	(0.0127)
Pre-tsunami boat length	0.00227	0.000167	0.00211
	(0.00153)	(0.00506)	(0.00534)
Poor	0.0413*	-0.222**	-0.223**
	(0.0231)	(0.0874)	(0.0896)
Low income	0.0533**	-0.159*	-0.156*
	(0.0216)	(0.0834)	(0.0862)
Middle income	0.0229	-0.188**	-0.192**
	(0.0310)	(0.0838)	(0.0861)
Household size	0.00191	-0.00293	-0.00589
	(0.00423)	(0.0109)	(0.0112)
Father was fishermen	-0.0310	0.0622	0.0794
	(0.0258)	(0.0663)	(0.0675)
Boat owner	-0.0703***		
	(0.0125)		
Wife attends arisan meetir	0.0219		
	(0.0148)		
Attends fishermen meetin;	-0.0184		
	(0.0183)		
Bank savings		-0.131***	-0.136***
		(0.0446)	(0.0457)
Sub-district FE	No	Yes	Yes
Interview month FE	No	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	705	535	530

Note: Marginal effects are reported.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.10: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats (unweighted)

	(1)	(2)	(3)	(4)	(5)
VARIABLES				1st stage	IV
	Current boat length		Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami productivity (residuals)	-0.0925		-0.0825*	-0.0986	-0.0609
	(0.0700)		(0.0458)	(0.0727)	(0.0460)
b: Pre-tsunami productivity (residuals) X Yr_{2009}	0.0951		0.117*	0.0913	0.0925
	(0.0945)		(0.0708)	(0.104)	(0.0698)
c: Pre-tsunami productivity (residuals) X Yr_{2012}	0.257**		0.134**	0.289**	0.0735
	(0.100)		(0.0670)	(0.116)	(0.0687)
d: Pre-tsunami boat length		0.242**			
		(0.117)			
e: Pre-tsunami boat length X Yr_{2009}		-0.0680			
		(0.0855)			
f: Pre-tsunami boat length X Yr_{2012}		0.0160			
		(0.122)			
Boat aid (dummy)	-4.967***	-5.086***	-1.099***	-4.919***	-0.0183
	(0.774)	(0.691)	(0.335)	(0.745)	(0.219)
g: Aid boat length	0.691***	0.673***	0.126***	0.646***	
	(0.126)	(0.107)	(0.0423)	(0.0770)	
h: Aid boat length X Yr_{2009}	0.103	0.106	0.0451		
	(0.107)	(0.103)	(0.0425)		
i: Aid boat length X Yr_{2012}	-0.219*	-0.207*	0.00803		
	(0.128)	(0.123)	(0.0466)		
j: Current boat length(instrumented)					0.171**
					(0.0688)
k: Current boat length(instrumented) X Yr_{2009}					0.102*
					(0.0607)
l: Current boat length(instrumented) X Yr_{2012}					0.0351
					(0.0775)
Constant	7.047***	5.636***	13.45***	7.253***	12.04***
	(0.803)	(0.876)	(0.573)	(0.651)	(0.736)
Chi squared statistic of testing:					
a = a+b =a+ c	6.60**	-	5.16*	-	2.17
d =d+e = d+f	-	0.99	-	-	-
g =g+h = g+i	5.85*	6.21**	1.66	-	-
j =j+k = j+l	-	-	-	-	3.52
Aid boat length (instrument) = 0	-	-	-	70.27***	-
Observations	264	499	262	264	262

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Table 2.11: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats (weighted to control for selection into the full sample)

	(1)	(2)	(3)	(4)	(5)
VARIABLES				1st stage	IV
	Current boat length		Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami productivity (residuals)	-0.0476		-0.129*	-0.0573	-0.123*
	(0.0891)		(0.0668)	(0.0938)	(0.0712)
b: Pre-tsunami productivity (residuals) X Yr_{2009}	0.0654		0.190*	0.0580	0.182*
	(0.130)		(0.0969)	(0.140)	(0.0989)
c: Pre-tsunami productivity (residuals) X Yr_{2012}	0.221		0.197**	0.252*	0.142
	(0.140)		(0.0955)	(0.149)	(0.0994)
d: Pre-tsunami boat length		0.420**			
		(0.164)			
e: Pre-tsunami boat length X Yr_{2009}		-0.193			
		(0.179)			
f: Pre-tsunami boat length X Yr_{2012}		-0.211			
		(0.165)			
Boat aid (dummy)	-4.895***	-4.427***	-0.987***	-4.783***	0.0451
	(0.806)	(0.727)	(0.348)	(0.977)	(0.236)
g: Aid boat length	0.677***	0.695***	0.117**	0.628***	
	(0.101)	(0.0894)	(0.0542)	(0.108)	
h: Aid boat length X Yr_{2009}	0.0899	0.00748	0.0265		
	(0.121)	(0.120)	(0.0561)		
i: Aid boat length X Yr_{2012}	-0.173	-0.259**	0.0366		
	(0.120)	(0.105)	(0.0544)		
j: Current boat length(instrumented)					0.145
					(0.0910)
k: Current boat length(instrumented) X Yr_{2009}					0.111
					(0.0973)
l: Current boat length(instrumented) X Yr_{2012}					0.0938
					(0.101)
Constant	7.063***	3.176**	13.47***	7.195***	12.29***
	(0.844)	(1.414)	(0.668)	(0.767)	(0.954)
Chi squared statistic of testing:					
a = a+b =a+ c	1.26	-	2.83*	-	1.90
d =d+e = d+f	-	0.85	-	-	-
g =g+h = g+i	2.17	3.22**	0.23	-	-
j =j+k = j+l	-	-	-	-	0.7
Aid boat length (instrument) = 0	-	-	-	33.53***	-
Observations	201	209	196	201	196

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Table 2.12: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats (weighted to control for selection into fishing)

	(1)	(2)	(3)	(4)	(5)
VARIABLES				1st stage	IV
	Current boat length		Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami productivity (residuals)	-0.102		-0.141**	-0.112	-0.109*
	(0.115)		(0.0596)	(0.114)	(0.0610)
b: Pre-tsunami productivity (residuals) X Yr_{2009}	0.109		0.171*	0.129	0.127
	(0.138)		(0.0898)	(0.133)	(0.0899)
c: Pre-tsunami productivity (residuals) X Yr_{2012}	0.398**		0.281***	0.431***	0.168
	(0.165)		(0.108)	(0.164)	(0.111)
d: Pre-tsunami boat length		0.236*			
		(0.137)			
e: Pre-tsunami boat length X Yr_{2009}		-0.125			
		(0.162)			
f: Pre-tsunami boat length X Yr_{2012}		-0.0553			
		(0.153)			
Boat aid (dummy)	-3.780***	-3.605***	-0.871**	-4.037***	0.0996
	(0.868)	(0.833)	(0.359)	(0.902)	(0.232)
g: Aid boat length	0.458**	0.442**	0.109**	0.538***	
	(0.197)	(0.191)	(0.0459)	(0.114)	
h: Aid boat length X Yr_{2009}	0.221	0.215	0.0363		
	(0.171)	(0.191)	(0.0470)		
i: Aid boat length X Yr_{2012}	-0.0221	-0.0644	0.0347		
	(0.182)	(0.179)	(0.0483)		
j: Current boat length(instrumented)					0.208**
					(0.0817)
k: Current boat length(instrumented) X Yr_{2009}					0.0840*
					(0.0452)
l: Current boat length(instrumented) X Yr_{2012}					0.0230
					(0.101)
Constant	8.190***	6.431***	13.26***	7.875***	11.41***
	(1.206)	(1.388)	(0.741)	(0.812)	(0.983)
Chi squared statistic of testing:					
a = a+b =a+ c	3.16**	-	3.93**	-	1.55
d =d+e = d+f	-	0.35	-	-	-
g =g+h = g+i	2.11	1.86	0.37	-	-
j =j+k = j+l	-	-	-	-	1.88
Aid boat length (instrument) = 0	-	-	-	22.27***	-
Observations	202	208	199	202	199

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Table 2.13: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats (weighted to control for selection into aid application)

	(1)	(2)	(3)	(4)	(5)
VARIABLES				1st stage	IV
	Current boat length		Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami productivity (residuals)	-0.0821		-0.114	-0.0827	-0.0923
	(0.125)		(0.0737)	(0.127)	(0.0761)
b: Pre-tsunami productivity (residuals) X Yr_{2009}	0.0645		0.147	0.0391	0.125
	(0.145)		(0.105)	(0.152)	(0.105)
c: Pre-tsunami productivity (residuals) X Yr_{2012}	0.254		0.265**	0.282	0.204*
	(0.179)		(0.118)	(0.177)	(0.120)
d: Pre-tsunami boat length		0.353**			
		(0.178)			
e: Pre-tsunami boat length X Yr_{2009}		-0.178			
		(0.185)			
f: Pre-tsunami boat length X Yr_{2012}		-0.105			
		(0.184)			
Boat aid (dummy)	-4.612***	-3.752***	-0.797**	-4.604***	0.0718
	(0.773)	(0.767)	(0.331)	(0.909)	(0.220)
g: Aid boat length	0.650***	0.551***	0.0894**	0.633***	
	(0.144)	(0.166)	(0.0445)	(0.108)	
h: Aid boat length X Yr_{2009}	0.104	0.115	0.0572		
	(0.124)	(0.152)	(0.0442)		
i: Aid boat length X Yr_{2012}	-0.141	-0.145	0.0390		
	(0.151)	(0.157)	(0.0486)		
j: Current boat length(instrumented)					0.115*
					(0.0693)
k: Current boat length(instrumented) X Yr_{2009}					0.138**
					(0.0623)
l: Current boat length(instrumented)* X Yr_{2012}					0.0688
					(0.0811)
Constant	6.872***	4.497***	13.44***	6.909***	12.40***
	(0.877)	(1.407)	(0.764)	(0.789)	(0.925)
Chi squared statistic of testing:					
a = a+b =a+ c	1.05	-	2.71*	-	1.59
d =d+e = d+f	-	0.52	-	-	
g =g+h = g+i	2.22	2.03	0.85	-	2.49*
j =j+k = j+l	-	-	-	-	-
Aid boat length (instrument) = 0	-	-	-	34.67***	-
Observations	213	222	209	213	209

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Table 2.14: Impact of Boat Aid and Pre-Tsunami Boat Length on Current Boat Length

	(1)	(2)	(3)	(4)
VARIABLES	Sample (lost boats)		Sample (survived boats)	
	Current boat length			
a: Pre-tsunami boat length	0.268**	0.270**	0.661***	0.671***
	(0.108)	(0.111)	(0.101)	(0.0915)
b: Aid boat length	0.171**	0.170**	0.0875	0.0224
	(0.0818)	(0.0851)	(0.0872)	(0.0526)
Age		0.0275		0.0976
		(0.0789)		(0.406)
Age squared		-0.000435		-0.000653
		(0.000873)		(0.00449)
Father was a fisherman		-0.264		3.113*
		(0.333)		(1.775)
Constant	4.134***	3.779**	1.240	-3.378
	(0.655)	(1.786)	(0.903)	(9.069)
Sub-district FE	Yes	Yes	Yes	Yes
F-statistcs of testing:				
a=1	45.87***	43.62***	11.23***	12.91***
b=0	4.35**	4.01**	1.01	0.18
a=b	0.33	0.32	24.52***	46.84***
Observations	250	241	44	44
R-squared	0.434	0.439	0.733	0.810

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Within the pooled sample, the sub-sample of fishermen with surviving boats are weighted to control for selection into aid application. The sub-sample of fishermen with lost boats are unweighted (the weights are set to one).

Table 2.15: Impact of Boat Aid and Pre-Tsunami Boat Length on Current Boat Length (sample with no aid boat is use)

	(1)	(2)	(3)	(4)
VARIABLES	Sample (lost boats)		Sample (survived boats)	
	Current boat length			
a: Pre-tsunami boat length	0.360***	0.359***	0.676***	0.673***
	(0.121)	(0.123)	(0.128)	(0.120)
b: Aid boat length	0.157**	0.155*	0.0963	0.0231
	(0.0793)	(0.0823)	(0.106)	(0.0652)
Age		0.0116		0.0929
		(0.0932)		(0.422)
Age squared		-0.000316		-0.000590
		(0.00103)		(0.00472)
Father was a fisherman		-0.409		3.096*
		(0.384)		(1.814)
Constant	3.672***	3.814*	1.125	-3.314
	(0.718)	(2.110)	(1.122)	(9.225)
Sub-district FE	Yes	Yes	Yes	Yes
F-statistcs of testing:				
a=1	27.85***	27.02***	6.35**	7.38**
b=0	3.93**	3.56*	0.83	0.12
a=b	1.28	1.21	25.38***	39.26***
Observations	199	193	42	42
R-squared	0.415	0.423	0.721	0.784

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Within the pooled sample, the sub-sample of fishermen with surviving boats are weighted to control for selection into aid application. The sub-sample of fishermen with lost boats are unweighted (the weights are set to one).

2.6 Appendix A

This model closely follows the one in de Mel et al. (2008) but also draws on Fafchamps et al. (2014). The key assumption is that fishermen are endowed with heterogeneous fishing ability, θ_j. Consider the absence of aid boats. Taking initial levels of capital, $k_{j,1}$, asset, $b_{j,1}$, and interest rates, $\{i_t\}_{t=1}^{\infty}$, as given, fisherman j's problem is to choose $\{c_{j,t}, k_{j,t+1}, b_{j,t+1}\}_{t=1}^{\infty}$ to maximize his lifetime welfare

$$\sum_{t=1}^{\infty} \beta^{t-1} u(c_{j,t}) \tag{2.12}$$

subject to

$$c_{j,t} + k_{j,t+1} + b_{j,t+1} \leq f(k_{j,t}, \theta_j) + k_{j,t} + (1 + i_t) b_{j,t} \tag{2.13}$$

where $f(k_{j,t}, \theta_j)$ is the production function of fishing. First-order conditions with respect to consumption, $c_{j,t}$, capital, $k_{j,t+1}$, and asset, $b_{j,t+1}$, are:

$$\lambda_t = u'(c_{j,t}) \tag{2.14}$$

$$\lambda_t = \beta \lambda_{t+1} [1 + \partial f(k_{j,t+1}, \theta_j) / \partial k_{j,t+1}] \tag{2.15}$$

$$\lambda_t = \beta \lambda_{t+1} (1 + i_{t+1}) \tag{2.16}$$

Thus, equations (2.15) and (2.16) imply

$$\partial f(k_{j,t+1}, \theta_j)/\partial k_{j,t+1} = i_{t+1} \tag{2.17}$$

That is, at the the optimum, fisherman j sets the net return to investment to zero such that the marginal revenue of capital is equal to the market interest rate of asset.

Let the production function of fishing assume the Cobb-Douglas functional form with constant returns to scale:

$$f(k_{j,t}, \theta_j) = k_{j,t}^{\alpha}\theta_j^{1-\alpha} \tag{2.18}$$

Here, the parameter $\alpha \in (0, 1)$ represents the share of capital in fishing. Let $k^*_{j,t}$ denote the optimal level of capital for fisherman j. Equations (2.18) and (2.19) allow us to express $k^*_{j,t}$ as follows:

$$k^*_{j,t} = \theta_j \left[\frac{\alpha}{i_t}\right]^{\frac{1}{1-\alpha}} \tag{2.19}$$

Hence, the optimal level of capital is increasing in inherent fisherman ability, θ_j, and the output elasticity of capital, α, but decreasing in the interest rate, i_t. Equations (2.18) and (2.19) show that at the optimum, inherent fishing ability, θ_j, has a direct impact on the production function as well as an indirect effect through the capital stock.

Next, consider the presence of boat aid in post-tsunami Aceh. Let t be the period when aid boats are distributed. If fisherman j receives an aid boat, then

$k_{j,t} = k_{aid}$. His production function becomes:

$$f(k_{j,t}, \theta_j) = k_{aid}^{\alpha} \theta_j^{1-\alpha} \tag{2.20}$$

Since k_{aid} is exogenous, inherent fishing ability, θ_j, now only has a direct impact on the production function. Thus, I can empirically separate the effect of capital on fishing production from the effect of inherent fishing ability. In Section 2.4, I present empirical evidence that while returns to aid boats, whose quality I measure with boat length, and inherent fishing ability are both positive, the former diminishes over time, i.e. $\partial^2 f(k_{j,t}, \theta_j)/\partial k_{j,t}^2 < 0$; while the latter increases, i.e. $\partial^2 f(k_{j,t}, \theta_j)/\partial \theta_j^2 > 0$. Reduced-form estimates of $\partial f(k_{i,t}, \theta_j)/\partial k_{aid}$ and $\partial f(k_{j,t}, \theta_j)/\partial \theta_j$ are presented in Section 2.4.1.

2.7 Appendix B

Table 2.16: Descriptive Statistics among Attrited and Non-Attrited Sample

	(1)	(2)	(3)
VARIABLES	A: Sample (Stayers)	B: Sample (Attrited)	A-B
Pre-tsunami characteristics:			
Productivity (residuals)	-0.0233	0.460	-0.483
	(0.0908)	(0.390)	(0.413)
Boat length	8.920	8.726	0.194
	(0.214)	(0.268)	(0.359)
Indebted	0.332	0.257	0.0754*
	(0.0247)	(0.0328)	(0.0421)
Age	41.55	41.253	0.297
	(0.577)	(0.806)	(1.000)
Household size	3.942	4.782	-0.840***
	(0.0939)	(0.132)	(0.163)
No school	0.0444	0.0411	0.00328
	(0.0112)	(0.0165)	(0.0202)
Elementary	0.537	0.479	0.0572
	(0.0288)	(0.0415)	(0.0505)
Junior high school	0.217	0.295	-0.0779*
	(0.0238)	(0.0379)	(0.0432)
Senior high school or above	0.163	0.185	-0.0216
	(0.0214)	(0.0322)	(0.0380)
Father was a fisherman	0.0567	0.00685	0.0498**
	(0.0134)	(0.00685)	(0.0198)
Wife attends *arisan* meetings	0.242	0.218	0.0239
	(0.0225)	(0.0309)	(0.0387)
Number of income earners	1.571	1.559	0.0128
	(0.0524)	(0.0668)	(0.0882)
Observations	**363**	**179**	**-**

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.17: Testing the Equality of Coefficients: Impact of Boat Aid on Post-Tsunami Performance (pooled sample)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Sample (lost boats)			Sample (survived boats)		
	Current boat length		Log of revenue	Current boat length		Log of revenue
Pre-tsunami productivity (residuals)	-0.0415		-0.0756	0.772		0.0315
	(0.0708)		(0.0506)	(0.798)		(0.118)
Pre-tsunami productivity (residuals) X Yr_{2009}	-0.0515		0.0829	-0.524		-0.202
	(0.124)		(0.0763)	(1.004)		(0.192)
Pre-tsunami productivity (residuals) X Yr_{2012}	0.186		0.110	-0.730		-0.0846
	(0.124)		(0.0781)	(0.967)		(0.203)
Pre-tsunami boat length		0.361***			0.569***	
		(0.137)			(0.198)	
Pre-tsunami boat length X Yr_{2009}		-0.148			0.0260	
		(0.159)			(0.203)	
Pre-tsunami boat length X Yr_{2012}		0.0579			-0.0738	
		(0.203)			(0.209)	
Boat aid (dummy)	-5.622***	-3.920***	-1.278***	-4.600***	-4.312***	-0.850*
	(0.709)	(0.659)	(0.266)	(1.760)	(1.102)	(0.434)
Aid boat length	0.768***	0.643***	0.155***	0.568**	0.429**	0.0738
	(0.119)	(0.125)	(0.0408)	(0.264)	(0.194)	(0.0627)
Aid boat length X Yr_{2009}	-0.0406	0.0913	-0.0211	-0.0570	-0.112	0.0265
	(0.117)	(0.146)	(0.0372)	(0.171)	(0.171)	(0.0459)
Aid boat length X Yr_{2012}	-0.205	-0.221	-0.00519	-0.0951	-0.00692	0.0186
	(0.128)	(0.158)	(0.0452)	(0.189)	(0.182)	(0.0595)
Constant	6.498***	2.810**	14.14***	6.498***	2.810**	14.14***
	(1.066)	(1.174)	(0.357)	(1.066)	(1.174)	(0.357)
Hypothesis (coefficients are equal between sample):						
Pre-tsunami productivity (residuals)	1.08		0.68	1.08		0.68
Pre-tsunami productivity (residuals) X Yr_{2009}	0.21		1.87	0.21		1.87
Pre-tsunami productivity (residuals) X Yr_{2012}	0.91		0.84	0.91		0.84
Pre-tsunami boat length		1.32			1.32	
Pre-tsunami boat length X Yr_{2009}		0.73			0.73	
Pre-tsunami boat length X Yr_{2012}		0.37			0.37	
Boat aid (dummy)	0.41	0.13	1.17	0.41	0.13	1.17
Aid boat length	0.79	0.85	1.85	0.79	0.85	1.85
Aid boat length X Yr_{2009}	0.02	0.71	1.41	0.02	0.71	1.41
Aid boat length X Yr_{2012}	0.68	0.69	0.27	0.68	0.69	0.27
Observations	354	589	352	354	589	352

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.
The model is estimated on the pooled sample. Coefficients are reported separately for each sample. Within the pooled sample, the sub-sample of fishermen with surviving boats are weighted by inverse probability weights that control for selection into aid application. The sub-sample of fishermen with lost boats are unweighted (the weights are set to one).

Table 2.18: Impact of Boat Aid on Post-Tsunami Performance (pooled sample)

	(1)	(2)	(3)	(4)	(5)
VARIABLES				1st stage	IV
	Current boat length		Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami productivity (residuals)	-0.0718		-0.0422	-0.0995	-0.0205
	(0.156)		(0.0468)	(0.165)	(0.0477)
b: Pre-tsunami productivity (residuals) X Yr_{2009}	0.0471		-0.0127	0.0749	-0.0384
	(0.212)		(0.0738)	(0.236)	(0.0743)
c: Pre-tsunami productivity (residuals) X Yr_{2012}	0.120		0.0553	0.210	0.00968
	(0.219)		(0.0749)	(0.238)	(0.0752)
d: Pre-tsunami boat length		0.341**			
		(0.160)			
e: Pre-tsunami boat length X Yr_{2009}		0.0277			
		(0.186)			
f: Pre-tsunami boat length X Yr_{2012}		0.0914			
		(0.183)			
Boat aid (dummy)	-5.836***	-5.216***	-1.125***	-5.569***	-0.00212
	(0.832)	(0.699)	(0.270)	(0.898)	(0.177)
g: Aid boat length	0.803***	0.718***	0.128***	0.637***	
	(0.115)	(0.101)	(0.0382)	(0.102)	
h: Aid boat length X Yr_{2009}	-0.142	-0.149	0.000624		
	(0.138)	(0.117)	(0.0344)		
i: Aid boat length X Yr_{2012}	-0.273*	-0.256**	0.00349		
	(0.144)	(0.116)	(0.0432)		
j: Current boat length(instrumented)					0.121
					(0.0748)
k: Current boat length(instrumented) X Yr_{2009}					0.119*
					(0.0682)
l: Current boat length(instrumented) X Yr_{2012}					0.0647
					(0.0802)
Constant	4.772***	2.972**	14.19***	4.915***	13.58***
	(1.362)	(1.507)	(0.319)	(1.496)	(0.475)
Chi squared statistic of testing:					
a = a+b =a+ c	0.16	-	0.39		0.20
d =d+e = d+f	-	0.18	-	-	-
g =g+h = g+i	1.81	2.43*	0.00	-	-
j =j+k = j+l	-	-	-	-	1.59
Aid boat length (instrument) = 0	-	-	-	39.08***	-
Observations	397	633	358	397	358

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects. Within the pooled sample, the sub-sample of fishermen with surviving boats are weighted by inverse probability weights that control for selection into aid application. The sub-sample of fishermen with lost boats are unweighted (the weights are set to one).

Table 2.19: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats using CES Productivity Measure (unweighted)

	(1)	(2)	(3)	(4)
VARIABLES			1st stage	IV
	Current boat length	Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami CES productivity (residuals)	-0.0793	-0.0800*	-0.0855	-0.0604
	(0.0654)	(0.0457)	(0.0685)	(0.0456)
b: Pre-tsunami CES productivity (residuals) X Yr_{2009}	0.0883	0.115	0.0865	0.0915
	(0.0947)	(0.0711)	(0.105)	(0.0697)
c: Pre-tsunami CES productivity (residuals) X Yr_{2012}	0.249**	0.131**	0.281**	0.0709
	(0.0993)	(0.0664)	(0.115)	(0.0680)
Boat aid (dummy)	-4.968***	-1.101***	-4.919***	-0.0199
	(0.775)	(0.335)	(0.747)	(0.220)
g: Aid boat length	0.692***	0.126***	0.646***	
	(0.126)	(0.0423)	(0.0769)	
h: Aid boat length X Yr_{2009}	0.103	0.0453		
	(0.107)	(0.0424)		
i: Aid boat length X Yr_{2012}	-0.219*	0.00830		
	(0.128)	(0.0466)		
j: Current boat length(instrumented)				0.171**
				(0.0687)
k: Current boat length(instrumented) X Yr_{2009}				0.102*
				(0.0604)
l: Current boat length(instrumented) X Yr_{2012}				0.0358
				(0.0774)
Constant	11.70***	14.29***	11.60***	12.04***
	(0.799)	(0.620)	(0.771)	(0.734)
Chi squared statistic of testing:				
a = a+b =a+ c	6.28**	4.99*	-	2.11
g =g+h = g+i	5.86*	1.67	-	-
j =j+k = j+l	-	-	-	3.54
Aid boat length (instrument) = 0	-	-	70.48***	-
Observations	264	262	264	262

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Table 2.20: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats using Per Unit Productivity Measure (unweighted)

	(1)	(2)	(3)	(4)
VARIABLES			1st stage	IV
	Current boat length	Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami per unit productivity (residuals)	-0.0867	-0.0760*	-0.0927	-0.0552
	(0.0693)	(0.0457)	(0.0720)	(0.0457)
b: Pre-tsunami per unit productivity (residuals) X Yr_{2009}	0.0912	0.111	0.0871	0.0867
	(0.0949)	(0.0705)	(0.105)	(0.0694)
c: Pre-tsunami per unit productivity (residuals) X Yr_{2012}	0.253**	0.128*	0.285**	0.0678
	(0.0998)	(0.0664)	(0.115)	(0.0680)
Boat aid (dummy)	-4.969***	-1.101***	-4.922***	-0.0180
	(0.776)	(0.335)	(0.747)	(0.220)
g: Aid boat length	0.692***	0.126***	0.646***	
	(0.126)	(0.0424)	(0.0770)	
h: Aid boat length X Yr_{2009}	0.103	0.0452		
	(0.107)	(0.0426)		
i: Aid boat length X Yr_{2012}	-0.219*	0.00809		
	(0.128)	(0.0467)		
j: Current boat length(instrumented)				0.172**
				(0.0690)
k: Current boat length(instrumented) X Yr_{2009}				0.102*
				(0.0610)
l: Current boat length(instrumented) X Yr_{2012}				0.0352
				(0.0777)
Constant	11.70***	14.29***	11.60***	12.04***
	(0.800)	(0.618)	(0.772)	(0.735)
Chi squared statistic of testing:				
a = a+b =a+ c	6.44**	4.78*	-	1.93
g =g+h = g+i	5.85*	1.65	-	-
j =j+k = j+l	-	-	-	3.49
Aid boat length (instrument) = 0	-	-	70.37***	-
Observations	264	262	264	262

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Table 2.21: Impact of Boat Aid on Post-Tsunami Performance among Fishermen with Lost Boats (in Kecamantan with <100% Aid)

	(1)	(2)	(3)	(4)	(5)
VARIABLES				1st stage	IV
	Current boat length		Log fishing revenue	Current boat length	Log fishing revenue
a: Pre-tsunami productivity (residuals)	-0.115		-0.114	-0.132	-0.0794
	(0.111)		(0.0736)	(0.117)	(0.0755)
b: Pre-tsunami productivity (residuals) X Yr_{2009}	0.153		0.196**	0.156	0.147
	(0.147)		(0.0969)	(0.162)	(0.0983)
c: Pre-tsunami productivity (residuals) X Yr_{2012}	0.324**		0.275***	0.362**	0.195*
	(0.161)		(0.101)	(0.180)	(0.108)
d: Pre-tsunami boat length		0.272**			
		(0.137)			
e: Pre-tsunami boat length X Yr_{2009}		-0.0715			
		(0.0927)			
f: Pre-tsunami boat length X Yr_{2012}		0.0182			
		(0.132)			
Boat aid (dummy)	-5.118***	-4.830***	-1.007***	-5.127***	0.0342
	(0.835)	(0.741)	(0.356)	(0.811)	(0.226)
g: Aid boat length	0.687***	0.629***	0.114**	0.663***	
	(0.133)	(0.126)	(0.0444)	(0.0870)	
h: Aid boat length X Yr_{2009}	0.102	0.104	0.0465		
	(0.110)	(0.115)	(0.0437)		
i: Aid boat length X Yr_{2012}	-0.167	-0.164	0.0187		
	(0.134)	(0.132)	(0.0499)		
j: Current boat length(instrumented)					0.162**
					(0.0706)
k: Current boat length(instrumented) X Yr_{2009}					0.0928
					(0.0607)
l: Current boat length(instrumented) X Yr_{2012}					0.0268
					(0.0836)
Constant	10.34***	8.754***	13.86***	10.40***	11.95***
	(1.157)	(1.613)	(0.517)	(1.036)	(0.583)
Chi squared statistic of testing:					
a = a+b =a+ c	4.12	-	9.24***	-	4.11
d =d+e = d+f	-	0.95	-	-	-
g =g+h = g+i	3.47	3.86	1.29	-	-
j =j+k = j+l	-	-	-	-	2.93
Aid boat length (instrument) = 0	-	-	-	57.98***	-
Observations	215	343	216	215	216

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include sub-district (kecamantan), interview month, and year fixed effects.

Chapter 3: Household Responses to Natural Disasters: Labor Supply and Borrowing

3.1 Introduction

In this chapter, I explore the differences in behavior among Indonesian households before and after exposure to natural hazards. I focus on the following outcome variables of interest: market labor, voluntary labor, household-level borrowing through formal sources, and individual-level borrowing through informal sources. In addition, I examine whether there are gender differences in the changes of these outcomes. Specifically, by using household panel data from Indonesia in 1997, 2000, and 2007, I analyze the short-run (one year) weeks of work and borrowing responses to different types of natural hazards, including storms, floods, landslides, and earthquakes.

The focus on labor outcomes is related to the literature that examine the relationship among adult labor supply, wages, and income shocks. Kochar (1999), for example, explores the increase from farm to off-farm hours of work by Indian households after they experience household-specific shocks to crop income. Similarly, Rose (2001) demonstrates that Indian farm households are more likely to participate in the labor market in the aftermath of unexpected and negative rainfall shocks. Since natural hazards are locally aggregate shocks, a shift of labor from farm to off-farm activities would not alleviate the shock for households. Thus, instead of comparing labor supplied on-farm and off-farm, I focus on the specific intensive margin of wage labor by analyzing the quantity of paid labor supplied on the market among male and female household members in Indonesia.

More generally, this chapter contributes to the existing literature that study the determinants of occupational choice and labor supply. From a theoretical perspective, Banerjee and Newman (1993) build a model in which the the structure of occupational choice is determined by the initial distribution of wealth, but the process of development has an impact on this structure by changing the demand for and supply of different types and thus returns to labor and occupations.

Empirically, Bardhan (1979) is one of the first studies that uses micro-level data to estimate labor supply functions among agricultural households in a developing country context. By predicting the wage rate with a hypothetical minimum that is exogenously determined, Bardhan (1979) finds that the wage elasticity of supply is small. Instead, the author finds that labor supply, measured by the agricultural labor days supplied in a reference week, is more strongly determined by social and demographic conditions of the household. A limitation of this study is the use of cross-sectional data as it does not control for unobserved heterogeneity among households.

To identify the causal impacts of extreme weather events on household labor and borrowing in Indonesia, I first estimate the predicted number of hazards in each of the 216 districts (*kabupaten*) in each survey year using historical data from 1980 to 2008. I then take the residuals from these regressions as the unexpected number of hazards. Since changes in wage rates reflect shifts in both the demand and supply of labor, an OLS estimation of labor supply elasticities is likely to be biased downward (Oettinger 1999). Therefore, I account for the endogeneity of wages by using the sector-year-province average wage by gender to instrument for self-reported wages.

In contrast to the finding in Gagnon (2013) that wage labor supply in Honduras is not statistically different between municipalities with and without exposure to Hurricane Mitch in the short run, I find that women from districts with more unexpected disasters work 3% to 8% fewer weeks on the market, depending on the specification. However, I find no evidence of disaster-related changes in male labor supply. Unexpected disasters are also associated with higher probabilities of household-level borrowing and participation in rotating community credit groups, as well as larger loans.

The finding that women in districts with more unexpected disasters work fewer weeks as paid labor combined with the associated higher likelihood of borrowing and higher values of loan suggest that the substitution effect dominates the income effect. Consistent with the discussion in Jayachandran (2006), when labor productivity is low, adverse weather shocks may reduce the demand for agricultural labor, leading to a reduction in wages and labor supplied if households can borrow or smooth consumption by drawing on their savings.

The result that the male and female labor supply responses to natural hazards differ is consistent with the work done by Rosenzweig (1978) and Heckman (1993) showing that in developing countries, women face additional institutional constraints on their ability to adjust their labor supply on the market. Moreover, the focus on individual-level borrowing through informal sources is related to the literature that looks at the presence of risk-pooling among households as a coping mechanism against adverse shocks. Udry (1994), for example, shows that the realized rates of return are lower and the repayment periods are longer for Nigerian households that experience negative income shocks. This finding of state-contingent loans suggest that households do not only rely on ex-ante consumption-smoothing mechanisms such as saving, but also ex-post mechanisms to counter income fluctuations due to unexpected shocks.

The rest of the chapter is organized as follows: Section 3.2 presents a theoretical framework linking household behavior and natural hazards. Section 3.3 describes the household and disaster data. Section 3.4 presents the empirical strategy and Section 3.5 discusses the results. Section 3.6 concludes and discusses extensions of this study.

3.2 Theory

In this section, I briefly outline the theoretic channels linking natural hazards with each of the three outcomes of interest. First, natural disasters may affect household supply of labor on the market in various ways and the overall direction of the impact is ambiguous. If a natural disaster kills or injures a portion of the labor force, aggregate labor supply may fall and the wage increases, leading to an increase in household labor supply if the substitution effect dominates the income effect. Moreover, if a natural disaster causes physical damage to infrastructure that needs rebuilding, aggregate labor demand would increase and the wage also increases. However, if a natural disaster disrupts the transportation network such that the costs for certain households to get to work increase, household labor supply may be constrained to a sub-optimal level.

Within the same household, these possible links between natural hazards and labor supply may differ among men and women. For instance, the increase in wages due to a construction boom to rebuild damaged infrastructure is more likely to impact men because of higher demand for male labor in physically-demanding work. Meanwhile, women are more likely to contribute to the social aspects of reconstruction, such as childcare, household maintenance, and care of the elderly, due to existing social norms about their roles in society (Trohanis, Svetlosakova, and Carlsson-Rex 2011). Moreover, since women assume these traditional roles of care taking and securing household assets, they are more vulnerable to disasters because they tend to spend more time in their homes, which are often constructed from materials that do not withstand destruction from disasters. Appendix C presents a theoretical model that relates natural disasters with individual labor supply decisions under the assumption that these social norms are binding.

The second theoretical channel relates household borrowing and natural hazards. When households are hit by locally aggregate shocks such as natural hazards, the role of informal insurance may weaken because the majority of members within such networks are impacted simultaneously. Thus, households may resort to borrow through formal sources such as financial institutions and government borrowing programs, in addition to relying on unaffected neighbors. This chapter extends the work of Zylberberg (2010) and Czura and Klonner (2012) by distinguishing between the impact of natural hazards on household borrowing and individual participation in *arisan* meetings, a rotating credit group at the community level.

3.3 Data

3.3.1 Household Data

I use household data from the second, third and forth waves of the Indonesian Family Life survey (IFLS), collected in 1997, 2000 and in 2007, respectively. The first wave of the IFLS, conducted in 1993, is a socioeconomic and health survey based on a sample of households representing about 83% of the Indonesian population living in 13 of the nation's 26 provinces (Frankenberg and Karoly 1995). In 1997, IFLS2 relocated and reinterviewed 94% of IFLS1 households. In cases where survey respondents moved in the intervening years, interviews were conducted at the new locations provided that they lay within the 13 provinces enumerated in the first wave of the Survey. IFLS3 and IFLS4 have 95.3% and 93.6% of reinterview rates with IFLS1 households respectively. Among other topics, the Survey gathered data on community resources, individual demographics, adult and children characteristics, as well as household economy, including expenditures, labor and non-labor income, asset ownership, and borrowing.

For adult labor outcomes, all respondents above 15 years of age are asked to identify a primary job and, if applicable, a secondary job. Information about the nature of the job, sector of work, hours and weeks of work, as well as monthly and annual salary are available. There are three categories describing the nature of the job - self-employed, unpaid family worker, and working for government agencies or private companies. According to the definition of labor force characteristics from the Current Population Survey conducted by the US Bureau of Labor Statistics, the labor force is the sum of employed and unemployed persons. The former consists of persons who "do any work for pay or profit during a reference period; persons who did at least 15 hours of unpaid work per week in a family-operated enterprise, and persons who were temporarily absent from their regular jobs because of illness, vacation, bad weather, industrial dispute, or various personal reasons" (BLS 2013). Thus, I define an individual to be a participant in the labor force as long as she reports working for profit as a self-employed person or for wage or as an unpaid family worker with 15 or more hours of work per week.

In this chapter, I categorize labor force participation into three groups. The first group is market labor, for which I define as weeks worked as paid labor for the government, private companies, or self-employed persons for profit in non-agricultural businesses. The second group is domestic labor, for which I define as weeks worked as self-employed persons for profit in agricultural businesses or unpaid weeks worked for agricultural family businesses. The third group is other unpaid labor, for which I include uncompensated weeks worked for non-agricultural family businesses. In addition to formal labor, the Survey asks if respondents participate in various community groups in the past year, including voluntary labor[1] .

In terms of household financing options, the Survey collects information on participation in borrowing through various sources, including rotating credit schemes called *arisan* in Indonesia. *Arisan* is a group lottery conducted at periodic meetings, in which each member contributes a certain amount of money to a common pool given to the tenured member whose name is drawn at random. Table 3.1 lists all the sources of borrowing and percentages of households who borrow from these sources. Various purposes are reported for obtaining loans, including social ceremonies, personal expenses such as medication, education, as well as business expenses including the purchase of inputs, equipment, land and cattle.

3.3.2 Summary Statistics

I aggregate individual-level data to form an unbalanced[2] three-year panel, yielding samples of 15,218 adult respondents from 6,716 households in 1997, 16,950 respondents from 8,653 households in 2000 and 21,220 respondents from 10,991 households in 2007.

Tables 3.2 and 3.3 present descriptive statistics of the household sample. In terms of household composition and demographics, there are 48% men and 51% women, on average, in all three waves of the IFLS. Of these adults, over 60% are

[1] A detailed description of "voluntary labor" is not provided in the questionnaire. Instead, an example of voluntary labor cited is "cleaning up the village." Thus, I believe "voluntary labor" is a broad category that refers to any kind of labor that is unpaid, voluntary, and generally benefit the village.

[2] Analysis using a balance panel provides consistent results with that of an unbalanced panel. Since unbalanced households provide additional information and variation to the analysis, I present results from the unbalanced panel in the chapter.

married at the time of the survey and over 40% report having children residing in the household. In the analysis on labor outcomes, I restrict the sample to households with working age (15 to 65 years) adults. In these households, women are slightly older than men, with the average age at 33 for both gender. Men are more educated than women on average, with under 10% with no schooling, over 30% attended at most primary school, over 45% attended at most secondary school, and close to 10% of men attended university. By contrast, over 10% of women never attended school, over 30% attended at most primary school, under 45% attended at most secondary school, and under 8% attended university.

In terms of household economy, the 1997 data reflect the economic downturn due to the financial crisis, while the 2000 and 2007 data imply the trends of recovery. Non-labor income from the sale and rent revenue of assets average 2.79 million Rupiah[3] in 1997, 4.52 million Rupiah in 2000, and 3.83 million Rupiah in 2007. For household, farm and non-farm business assets, the lowest market values appear in 1997 and the highest values in 2000.

In terms of labor outcomes, participation in paid market work increases over time but the gender gap remains. While 32%, 40%, and 44% of women report positive weeks worked as paid market labor in the three respective survey years, 58%, 67%, and 68% of men do. In terms of work sectors, a third of the sample engages in agricultural work.

Conditional on participation as paid market labor, men work slightly more

[3]All monetary values are in real 2007 Rupiah. The current (December, 2013) exchange rate of Rupiah to US dollars is 1 IDR = 0.000082 USD.

yearly weeks than women on average. While women work 38.38, 35.28, and 40.21 weeks in 1997, 2000, and 2007; men work 39.52, 36.04, and 40.87 weeks. However, men earn a much higher weekly wage on average. Female weekly wage is 0.093 million Rupiah in 1997, representing only 66% of the male weekly wage at 0.14 million Rupiah. In subsequent years, the ratio of female to male weekly wage increases but never surpasses 70%. Female weekly wages are on average 52% and 68% of the male wages in 2000 and 2007, respectively.

The gender gap in labor force participation extends to the case of voluntary labor. While 81% of men report participating in voluntary labor in the year prior to the survey, ply 29% of women did in 1997. Participation in voluntary labor decreased in 2000, with 68% and 19% of male and female volunteers. Although voluntary work increased again in 2007, levels are still lower than in 1997, with 72% of male and 21% of female volunteers.

In terms of household finance, the extensive margin in household borrowing has decreased over time during the study period, from 38% in 1997, to 23% in 2000, and 18% in 2007. However, for households who borrow, the average amount of loan in real 2009 Rupiah has risen more than twofold from 3.745 million Rupiah in 1997, to 5.832 million Rupiah in 2000, and 9.470 million Rupiah in 2007. The size of these loans constitute 6%, 7%, and 12% of the market value of household assets in the respective years.

A similar trend appears in individual participation in *arisan*, a periodic and rotating credit group based on lottery. On average, there are 20 such meetings in a year across the survey years. A wide gender gap in both the participation and amount of monetary contribution exists throughout the study period. In 1997, 17% of male respondents attended at least one *arisan* meeting, while 38% of women did on average. Only 16% and 11% of men attended *arisan* in 2000 and 2007, while 39% and 32% of women did in the respective waves. Among those who participate in *arisan*, the average amount of money contributed at each meeting is similar across men and women. Male participants contribute 3.66 Rupiah on average in 1997 while female participants contribute 3.03 Rupiah. These amounts constitute roughly 31% and 42% of their weekly labor income. In subsequent survey years, the amount contributed increased at a rate of approximately 50%, with men contributing 5.34 and 7.7 Rupiah in 2000 and 2007, representing 13% and 32% of weekly labor income. Similarly, women contribute 4.99 and 7.67 Rupiah in the respective years, representing 22% and 47% of weekly labor income.

3.3.3 Disaster Data

Using data from the Indonesian National Board for Disaster Management (BNPB), I show in Figure 3.1 the distribution of natural hazards from 1900 to 2008 across districts by the number of events. I only include districts that are IFLS enumeration areas. Although the figure shows that the distribution of disaster events is non-random, there is variation in the degree of exposure to natural hazards among nearby IFLS regions. To control for this variation, I include district-level fixed effects in the empirical estimation (see Section 3.4 below).

To measure household exposure to natural hazards, I match the IFLS household data with the BNPB disaster data. I restrict the estimation sample to include only recorded natural hazards from 1980 to 2008. In addition, I exclude tsunamis and volcanic eruptions from the analysis due to their low-probability of occurrence. I also exclude forest fires because they are often non-random events that are caused, in part, by human activities. Finally, I exclude droughts because these events typically last a long period of time and it is difficult to estimate their causal impacts on individual- or household-level outcomes measured at specific, and often short, time intervals. Types of disasters that remain are earthquakes, floods, landslides, storms, and surges.

During this period, 1,106 events of these types have occurred in 216 districts. For each recorded event, the BNPB data also contain measures of vulnerability to disasters, such as the number of people dead, missing, injured, affected, and evacuated due to each natural hazard. Using this information, I construct a vulnerability index for each event by calculating the proportion of the district population who is affected by each of the categories.

3.3.4 Identification Strategy

In this study, the interview date and district of residence jointly determine a household's exposure to natural disasters. Table 3.4 shows the exposure of IFLS households and districts to these natural hazards in each of the survey years. The numbers demonstrate the limitations in using level shocks. First, the number of recorded events has increased significantly between 1997 to 2007 due to improvements in disaster detection and monitoring technology. Thus, the absolute number of realized events is a poor measurement of shock without taking into account the reporting bias.

In addition, empirical evidence from studies of property prices before and after natural disasters suggests that economic agents update their risk perceptions based on past experience of extreme weather outcomes (see e.g. Brookshire et al. 1985, Bin and Polasky 2004, Hallstrom and Smith 2005). Therefore, the impact of level shocks on household behavior ex-post may be biased due to possible ex-ante disaster-mitigating behavior for agents who form expectations of future outcomes. Informative rainfall forecasts, for example, may lead to anticipatory migration that is welfare-improving (Rosenzweig and Udry 2014).

Instead of level measures of disasters, I propose a two-step procedure to isolate the unanticipated portion of disaster shock. I exploit the historic nature of the BNPB disaster data and predict the number of disasters in each district in each year as a first step:

$$D_{kt} = \beta_0 + \beta_1 D_{k(t-1)} + \theta_t + \gamma_k + \nu_{kt} \tag{3.1}$$

In the baseline specification, D_{kt} is the total number of disasters that hit district k in year t where $t = 1980, 1980, ..., 2008$. θ_t and γ_k are year and district fixed effects. Column (1) of Table 3.5 shows the results of this estimation, with the one-year lagged total number of disasters being positively correlated with the realized number of disasters in the current year (statistically significant at the 1% level). Since the Least Square Dummy Variable (LSDV) estimator for dynamic panel data models is not consistent for finite T (length of the longitudinal component of the panel), I use Kiviet (1995)'s approximation to correct the bias. As Column (2) shows, the magnitude of the coefficient on the lagged total number of disasters is 45% larger with the Kiviet correction. In the second step, I regress individual and household outcomes on the resulting error terms, ν_{kt}, which capture the unexpected number of disasters for each household in each survey year.

3.4 Empirical Strategy

The central hypothesis of this chapter is that households change their behavior in response to natural hazards, including adjustments in labor supply, borrowing, and participation in *arisan*. I test this hypothesis empirically by comparing outcomes among households in districts with and without natural disasters.

3.4.1 Labor Outcomes

For labor market outcomes, I restrict the sample to men and women in joint-households with adult members who are of working age (between 15 and 65). Since the theoretical model in Appendix C suggests that natural disasters have no impacts on neither the slope nor the elasticity of male labor supply, male household members function as controls in the following analysis.

Market Labor Supply

To account for bias in the labor supply equations due to endogenous wages, I include several instruments. First, I include dummy variables for each household's main ethnic influence (28 dummies). Second, I estimate the male and female sector-year-province-average wages to control for sector-year-province-specific shocks in wages. Since this instrument varies at the province level, it captures variation in local wages due to variation in exposure and vulnerability to natural disasters. The first stage is estimated as follows:

$$logw_{it}^{f} = \zeta_0^{f} + \zeta_1^{f} log\bar{w}_{spt}^{f} + \alpha_2^{f} X_{it}^{f} + \alpha_3^{f} X_{it}^{m} + \alpha_4^{f} X_{ht} + \alpha_5^{f} X_{kt} + \theta_t + \sigma_h + \mu_{ihspt}^{f} \quad (3.2)$$

$$logw_{it}^{m} = \zeta_0^{m} + \zeta_1^{m} log\bar{w}_{spt}^{m} + \alpha_2^{m} X_{it}^{m} + \alpha_3^{m} X_{it}^{f} + \alpha_4^{m} X_{ht} + \alpha_5^{m} X_{kt} + \theta_t + \sigma_h + \mu_{ihspt}^{m} \quad (3.3)$$

where $\bar{w}_{spt}^{f}$ denotes the identifying instrument - the sector-year-province-average wage for females - and $\bar{w}_{spt}^{m}$ represents the equivalent for males. The parametric estimation of the male and female individual labor supply in the second stage is as follows:

$$weeks_{it}^{f} = \alpha_0^{f} + \alpha_1^{f} \widehat{logw_{it}^{f}} + \alpha_2^{f} X_{it}^{f} + \alpha_3^{f} X_{it}^{m} + \alpha_4^{f} X_{ht} + \alpha_5^{f} X_{kt} + \theta_t + \sigma_h + \mu_{iht}^{f} \quad (3.4)$$

$$weeks_{it}^{m} = \alpha_0^{m} + \alpha_1^{m} \widehat{logw_{it}^{m}} + \alpha_2^{m} X_{it}^{m} + \alpha_3^{m} X_{it}^{f} + \alpha_4^{m} X_{ht} + \alpha_5^{f} X_{kt} + \theta_t + \sigma_h + \mu_{iht}^{m} \quad (3.5)$$

Here, $weeks_{it}$ denotes the total number of weeks worked by individual i in household h at time t (where $t = 1997, 2000, 2007$). $\widehat{logw_{ht}^{i}}$ denotes the log of predicted weekly wage using instruments described above. The coefficient α_1 represents the strengths of substitution and income effects for market labor supply. A positive α_1 suggests a domination of the substitution effect over the income effect, and vice versa. X_{it}^f are control variables for female respondents, including her age, the squared of her age, her education, a dummy variable indicating whether she works in the agricultural sector, and her marital status . X_{it}^m is a vector of controls for her male partner who lives in the same household, including his wage, age, and education. If a woman lives with more than one man, then these variables are averaged over the total number of male household members. X_{ht} is a vector of variables on household characteristics, including non-labor income, number of children under five, number of children between the ages of six and 14, and total number of adult household members. X_{kt} is a vector of district-level variables, including dummies of whether the district is urban and coastal. I include time fixed-effects, θ_t, and household fixed effects, σ_h. The error terms u^f and u^m are clustered at the household level.[4]

To test the hypothesis that individual market labor supply before and after exposure to natural disasters differ, I estimate the following models:[5]

$$\begin{aligned} weeks_{it}^f = \alpha_0^f + \delta_1^f D_{hkt} + \delta_2^f V_{hkt} + \alpha_1^f \widehat{logw_{it}^f} + \alpha_2^f X_{it}^f \\ + \alpha_3^f X_{it}^m + \alpha_4^f X_{ht} + \alpha_5^f X_{kt} + \theta_t + \sigma_h + \mu_{hit}^f \end{aligned} \tag{3.6}$$

$$\begin{aligned} weeks_{it}^m = \alpha_0^m + \delta_1^m D_{hkt} + \delta_2^m V_{hkt} + \alpha_1^m \widehat{logw_{it}^f} + \alpha_2^f X_{it}^m \\ + \alpha_3^m X_{it}^m + \alpha_4^m X_{ht} + \alpha_5^m X_{kt} + \theta_t + \sigma_h + \mu_{iht}^m \end{aligned} \tag{3.7}$$

[4]As a robustness check, I also estimate the same equations with the error terms clustered at the district (*kabupaten*) level.

[5]In this and subsequent sections, when individual-level equations are specified, only the female equation with the superscript f is presented. The equivalent equation for men with the superscript m is also estimated.

where D_{hkt} is a vector of residuals from equation (3.1), representing the unpredicted number of disasters within a year of the interview date of household h in region k at time t. Since the IFLS interviews households over a period of several months in each survey year, I control for the time of interview in constructing D. If household h is interviewed anytime between July and December of year t, D_{kt} is assigned to this household; while $D_{k(t-1)}$ is assigned to households who are interviewed sometime between January and June of year t. Thus, households that reside in the same district may have different levels of exposure to disasters due to their specific interview dates within the survey period. V is a vector of vulnerability measures, including the average proportion of the population dead, missing, affected, injured, and evacuated in region k at time t across all disasters within one year of household h's interview date.

Volunteer Labor

In addition to market labor, I also examine the extent to which participation in unpaid, volunteer labor changes after natural disasters. I estimate the following probit model:

$$volunteer_{it}^{f} = a_0^f + b_1^f D_{hkt} + b_2^f V_{hkt} + a_2^f X_{it}^f + a_3^f X_{it}^m + a_4^f X_{ht} + a_5^f X_{kt} + \theta_t + \sigma_h + \mu_{hit}^f \quad (3.8)$$

where $volunteer_{it}^{f}$ is a dummy which equals one if woman i participated in volunteer labor in year t. I also estimate the equivalent model separately for men. A positive b_1 suggests that women in regions with more unpredicted natural disasters are more likely to participate in volunteer labor.

3.4.2 Borrowing

Besides labor outcomes, I examine whether households resort to borrow from formal sources and participate in rotating credit groups in the community to finance and cope with negative income shocks due to natural disasters. To examine borrowing outcomes, I estimate the following specification at the household level[6]:

$$Borrow_{ht} = c_0^f + \pi_1 D_{hkt} + \pi_2 V_{hkt} + c_2 I_{ht} + c_3 Finance_{ht} + c_4 X_{kt} + \theta_t + \sigma_h + \mu_{hit}^f \quad (3.9)$$

Here, $Borrow_{ht}$ is a dummy variable that equals one if household h has borrowed money in year t. I_{ht} denotes a vector of variables describing the household composition and demographics. Those variables include the number of adult members, children under five, and children between the ages of six and fifteen; a set of education dummies describing the highest level of education attended, including no schooling, primary education, secondary education, adult education, and college education, as well as the level and squared of the average age among adult members in the household. $Finance_{ht}$ is a vector of monetary variables describing the financial portfolio of the household, including non-labor income, as well as the market values of household assets, farm business assets, and non-farm business assets.

Further, I specify the household demand for credit through borrowing in the

[6]Information on individual borrowing is unavailable in the IFLS data, therefore, I conduct the analysis on borrowing at the household level.

following equation:

$$logloan_{ht} = d_0^f + \rho_1 D_{hkt} + \rho_2 V_{hkt} + d_2 I_{ht} + d_3 Finance_{ht} + d_4 X_{kt} + \theta_t + \sigma_h + \mu_{hit}^f \quad (3.10)$$

where $logloan_{ht}$ represents the amount borrowed by household h in year t in log form.

3.4.3 Participation in Arisan

To examine changes in the participation of *arisan* groups due to natural disasters, I estimate the following probit model at the individual level:

$$arisan_{it}^f = e_0^f + \mu_1^f D_{hkt} + \mu_2^f V_{hkt} + e_2^f X_{it}^f + e_3^f X_{ht} + e_4^f L_{ht} + e_5^f X_{kt} + \theta_t + \sigma_h + \mu_{hit}^f \quad (3.11)$$

where $arisan_{it}$ is a dummy variable that equals one if individual i participated in at least one *arisan* meeting in year t. L_{ht} is a vector of dummy variables that equal one if the household has at least one female member who works as a paid market worker, paid domestic worker, or an unpaid family worker.

I also specify the supply of *arisan* credit equation as follows:

$$a\_contribution_{it}^f = n_0^f + \lambda_1^f D_{hkt} + \lambda_2^f V_{hkt} + n_2^f X_{it}^f + n_3^f L_{ht} + n_4^f X_{kt} + \theta_t + \sigma_h + \mu_{hit}^f \quad (3.12)$$

where $arisan\_contribution_{it}$ represents the total amount contributed by individual i in all *arisan* meetings participated within year t.

3.5 Empirical Results

3.5.1 Labor Outcomes

Table 3.6 presents the results of the estimation of equation (3.6) in which I estimate the impact of natural disasters on annual weeks worked as paid market labor. The estimation sample consists of women who participate in the labor force as paid workers in non-agricultural sectors in all survey years. Since self-reported wages is endogenous in an estimation with the weeks worked in a year as the dependent variable, I use the sector-year-province average female wage as the identifying instrument for reported wages. Columns (1), (3) and (5) show the first stage estimations. In all models, F-tests show that the identifying instrument is strong and statistically significant at the 1% level.

Column (2) shows the results of an estimation of equation (3.6) that includes both the realized number of disasters in a district per survey year and the unexpected number, measured by the residuals of equation (3.1). Due to possible ex-ante disaster-mitigating behavior for agents who form expectations of future outcomes, the impact of level shocks on household behavior ex-post may be biased. Thus, the unexpected number of disasters represents plausibly exogenous disaster shocks. I find that while the realized number of disasters has a statistically zero impact on the number of weeks worked on the market by female household members, women in districts with an additional unexpected disaster work 8% fewer weeks year (significant at the 5% level). This result lends support to the notion that rational economic agents form expectations about weather outcomes and the unexpected outcomes, which are plausibly exogenous, lead to behavioral changes such as labor supplied on the market.

Column (4) shows the estimation results of equation (3.6) that includes both the expected and unexpected number of disasters for each district in each survey year. Consistent with the finding in column (2), women in districts with unexpected disaster shock works 3% fewer weeks than otherwise, while the coefficient on the expected number of disasters is statistically insignificant. Statistical tests show that I can reject equality of the expected and unexpected number of disasters.

Column (6) estimates equation (3.6) with only the unexpected number of disasters as a regressor of interest and I can reject that its impact on female labor supplied on the market is zero (significant at the 5% level). Specifically, I show that women respond to unexpected disasters in their districts of residence by working 3% fewer weeks a year.[7]

Table 3.7 shows the results of equation (3.7) in which I estimate the equivalent model for men. The use of the sector-year-province average wage for men is a strong instrument for self-reported wages. In contrast to female labor, I find that across all specifications, the effect of any unexpected disaster is statistically zero for men. These results imply that for individuals who already participate in the labor force as paid workers in non-agricultural sectors, unexpected disaster shock reduces the quantity of female labor supplied only with no impact on men.[8]

[7]Table 3.15 in Appendix F presents the results of estimating equation (3.6) with the standard errors clustered at the district (*kabupaten*) levels. The signs and magnitude of coefficients are consistent with those presented in Table 3.6.

[8]Table 3.16 in Appendix F presents the results of estimating equation (3.7) with the standard

Table 3.8 shows the results of a probit model that examines the impacts of natural hazards on participation in voluntary labor. Similar to market labor, I consider male and female voluntary labor participation separately. In contrast to the finding that female market labor responds to unexpected disasters, I find that districts with more expected disasters are associated with a reduction in the probability of women supplying voluntary labor (significant at the 5% level). The coefficient on unexpected disasters is positive but statistically zero. Statistical tests show that I can reject the impact of expected and unexpected disasters are identical. This result suggests that female market and voluntary labor supplied respond differently to unexpected weather outcomes. Only the former is affected. Columns (4) to (6) show that the coefficients of unexpected disasters on male participation in voluntary labor are negative but statistically zero.

3.5.2 Borrowing

Table 3.9 presents results of changes in household borrowing in the aftermath of natural hazards. While households do not resort to more borrowing in response to level shocks as shown in column (1), column (2) shows statistical evidence that households in districts with more unexpected disasters have higher probabilities of borrowing (significant at the 5% level). However, statistical tests fail to reject that the impact of expected and unexpected disasters have identical impacts on the probability of household borrowing.

errors clustered at the district (*kabupaten*) levels. The signs and magnitude of coefficients are consistent with those presented in Table 3.7.

Examining the intensive margins of borrowing, I do not find statistical evidence that borrowing households in districts with more level shocks obtain larger loans. Instead, households respond to unexpected shocks. Column (6) shows that households in districts with an unexpected disaster obtain loans that are 7% larger in value (significant at the 5% level). Controlling for disasters, households associated with more borrowing include those that are larger in size, with higher non-labor incomes, and have members with higher education. Moreover, households with more children, particularly those who are six years and older, obtain loans that are 63% higher (significant at the 1% level).

Table 3.10 shows results of individual participation and supply of credit in *arisan* meetings, a form of rotating community credit organization in Indonesia. Consistent with household borrowing, individual participation in *arisan* only responds positively to unexpected disaster shock, but not to level disaster shock as measured by the total number of disasters in a district per survey year (significant at the 5% levels). For individuals who participate in *arisan*, an individual contributes 6% less per meeting in districts with an unexpected disaster. In both the extensive and intensive margins, women are more likely to participate in *arisan* meetings than men of the same household. However, conditional on participation at these meetings, I do not find evidence that contributions by women and men are systematically different.

3.5.3 Robustness: Objective Measures of Disaster Intensity

As a robustness check, I explore the impact of the intensity of disasters on the main outcome variables of interest - market labor, voluntary labor, household borrowing and participation in *arisan* meetings - using objective measures rather than levels of severity that households self-report. Specifically, I restrict attention to earthquakes and floods as they each have well-defined and reliable measures of disaster intensity. Specifically, I use the Richter scale to measure the intensity of earthquakes and the flood magnitude, defined by the Dartmouth Flood Observatory, to measure the intensity of floods.[9] For each district in each survey year, I calculate the average magnitude for all earthquakes and floods.

Table 3.11 of Appendix F reports the impact of earthquake and flood intensity on female weeks worked in a year. In the first stage estimation, the sector-year-province average wage for females remain a strong instrument, with an F-statistic of 22.32 (significant at the 1% level). Column (2) reports the second stage estimation in which flood magnitude has a statistically zero impact on female labor supplied. In contrast, for each additional unit increase on the Richter scale for the average earthquake in a district, women work 0.03% fewer weeks on the market (significant at the 5% level). While this reduction in female labor supplied is consistent with that associated with unexpected disasters, the magnitude of the impact of earthquake intensity is small.

[9] As defined by the Dartmouth Flood Observatory, flood magnitude = log(duration x severity x affected area); severity: 1 = large flood events (1-2 decade return period); 1.5 = very large events (> 2 decades); 2 = extreme events (> 100 years). (See http://floodobservatory.colorado.edu/Archives/ArchiveNotes.html for details).

Table 3.12 repeats this analysis on male market labor. In contrast to the result for female market labor, I find that each additional unit increase on the Richter scale for the average earthquake in a district, men work 0.04% more weeks on the market (significant at the 5% level).[10]

In terms of voluntary labor, I show in Table 3.13 that the impact of flood and earthquake magnitudes have consistent impact on female voluntary labor but the opposite impact on male voluntary labor. Specifically, men and women who reside in districts with more serious earthquakes are more likely to participate in unpaid labor in the community (significant at the 1% and 10% levels). However, while women are more likely to participate in voluntary labor in districts that experience more serious floods (significant at the 5% level), I find a reduction in the probability of voluntary labor participation among men (significant at the 1% level). A possible interpretation of this contrasting result between male and female voluntary labor is that the majority of voluntary work in the aftermath of earthquakes are likely related to construction and rebuilding while that following floods is related to work that requires less physical labor, such as cleaning up debris on streets.

Finally, Table 3.14 shows that earthquake and flood intensity has statistically zero impact on household borrowing and individual participation in *arisan* meetings. This result complements the finding reported in Table 3.10, suggesting that household and individual borrowing are a function of the frequency but not the severity of natural disasters.

[10] I repeat the analysis with the standard errors clustered at the district (*kabupaten*) levels. Tables 3.17 and 3.18 in Appendix F display the results. The signs and magnitude of coefficients are consistent with those presented in Tables 3.11 and 3.12, respectively.

3.6 Conclusion

This chapter attempts to explore how households cope with natural hazards through behavioral adjustments ex-post. I focus on three outcomes: market and volunteer labor, borrowing, and informal credit. To isolate plausibly exogenous disaster shocks, I exploit the historic nature of disaster data to predict the number of disasters for each district in each year.

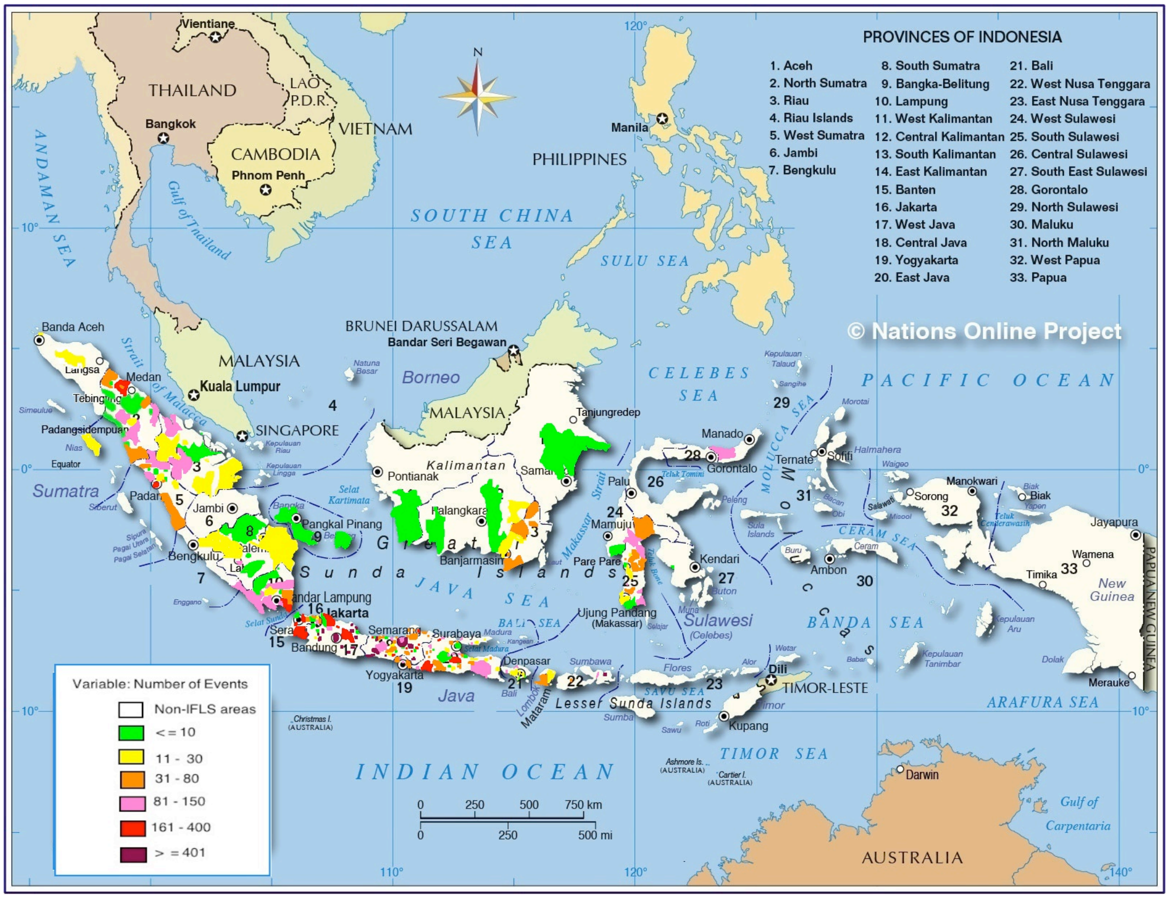
Two main patterns emerge in the results that are consistent across the three outcomes. First, households respond to unexpected rather than level shocks. Second, there are gender differences in the labor and informal credit outcomes. In particular, women from districts with more unexpected disasters work 3% to 8% fewer weeks a year as paid workers in non-agricultural sectors. Further, while more men supply voluntary labor than woman throughout the study period, unexpected disasters are associated with higher probabilities of participation in female voluntary labor only. I find no statistically significant impacts for men in either labor outcome.

In terms of participation in rotating credit groups, although women participate to a larger extent in both the extensive and intensive margins regardless of exposure to natural hazards, unexpected disaster shocks are associated with increased probabilities of attendance but lower-valued contributions per meeting for men and women.

Future work will extend the current analysis by analyzing the mechanisms behind the differential results between men and women in terms of market labor.

The first mechanism to examine is that there is a cultural reason for women to be restricted from working as paid labor on the market in the context of natural disasters. It is important to understand whether this restriction creates a welfare loss such that it bears the policy implication to lift the restrictions. An alternative mechanism is that women who live in districts with more unexpected disasters work less is a result of collective individual responses. For example, the marginal revenue from home production may increase in the aftermath of disasters such that the marginal revenue from working on the market is lower. Another possibility is that women's occupations on the market are systematically different from men's. If the majority of women are teachers, for example, a natural disaster that causes school closures may lead to reductions in labor supplied among a higher percentage of women and only a small share of male market labor.

Figure 3.1: Distribution of Natural Hazards in IFLS Districts from 1900 to 2008



Source: Author's calculation using the matched sample of Indonesian Family Life Survey and BNPB disaster database (http://www.bnpb.go.id). Map is from http://www.nationsonline.org/oneworld/map/indonesia_admin_map.htm.

Table 3.1: Main Sources of Loan and Distribution of Borrowing Households from Indonesia in 1997, 2000 and 2007

Sources of loan	% of borrowing households
Bank (private commercial, government, semi-government, agricultural)	48.88
Cooperative	25.49
Neighborhood association	0.53
Arisan	0.33
Money lender	10.97
Workplace	0.85
Pawnshop	0.90
Non-bank financial institution	4.24
Other	7.80

Note: Households can report multiple sources of loans, thus a sample of N borrowing households give rise to K>N observations in this column.

Source: Author's calculations using the 1997, 2000, and 2007 waves of the Indonesian Family Life Survey

Table 3.2: Summary Statistics - Household and Male Characteristics

	Mean			Standard Deviation		
	1997	2000	2007	1997	2000	2007
			A. Household			
# of adult household members	4.888	4.0322	5.4661	2.30	1.78	3.10
% of adult male household members	0.4831	0.4827	0.4935	0.50	0.50	0.50
# of children under 5 years old	0.5616	0.5782	0.5651	0.74	0.73	0.69
# of children between 6 to 14 years old	0.9790	0.8044	0.6974	1.051	1.00	0.86
Non-labor income	2.7891	4.5157	3.3831	5.948	7.496	6.8090
Household assets (market value)	57.7647	81.9426	75.9225	218.55	198.14	155.86
Farm business assets (market value)	26.0754	50.7579	48.0708	92.26	163.80	119.17
Non-farm business assets (market value)	16.8985	29.4615	22.7953	74.55	211.73	95.01
Borrowed money last year^	0.3815	0.2345	0.1756	0.4858	0.4374	0.3805
Amount borrowed last year	3.7451	3.7451	3.7451	15.200	38.20	33.30
			B. District			
Urban^	0.5119	0.5506	0.5814	0.50	0.50	0.49
Coastal^	0.4302	0.4609	0.4617	0.50	0.50	0.50
			C. Male			
Age	33.68	32.18	33.65	14.44	13.68	13.14
Highest level of education attended^						
No schooling	0.1051	0.0465	0.02183	0.31	0.21	0.15
Primary school	0.3388	0.3609	0.2996	0.47	0.48	0.46
Secondary school	0.4739	0.4993	0.5588	0.50	0.50	0.50
Adult education	0.0002545	0.00202	0.00913	0.0160	0.045	0.095
University	0.0814	0.09070	0.1107	0.27	0.29	0.31
Market work last year^	0.5808	0.6653	0.6804	0.49	0.47	0.47
Weekly wage	0.1417	0.2500	0.3030	0.21	0.61	0.57
Weeks worked in a year	39.52	36.04	40.87	14.67	16.69	14.01

Table 3.3: Summary Statistics - Male Characteristics (con't) and Female Characteristics

	Mean			Standard Deviation		
	1997	2000	2007	1997	2000	2007
	C. Male (con't)					
Participated in voluntary labor^	0.8124	0.6757	0.7154	0.39	0.47	0.45
Work in agricultural sector ^	0.4069	0.3738	0.2957	0.49	0.48	0.46
Currently married^	0.6108	0.6072	0.6748	0.49	0.49	0.47
Currently in school^	0.146	0.1283	0.1041	0.35	0.34	0.31
Participated in arisan^	0.1736	0.1575	0.1138	0.38	0.36	0.32
Amount contributed at each arisan meeting	0.0446	0.0651	0.0939	0.16	0.20	0.28
	D. Female					
Age	33.91	32.95	33.77	13.74	13.61	12.81
Highest level of education attended^						
No schooling	0.2262	0.1039	0.0581	0.42	0.31	0.23
Primary school	0.3129	0.4114	0.3466	0.46	0.49	0.48
Secondary school	0.3968	0.4145	0.489	0.49	0.49	0.5
Adult education	0.000515	0.0029	0.008	0.023	0.054	0.089
University	0.0633	0.0672	0.09834	0.24	0.25	0.3
Market work last year^	0.3202	0.4009	0.4422	0.47	0.49	0.5
Weekly wage	0.0934	0.1300	0.2058	0.18	0.13	0.48
Weeks worked in a year	38.38	35.28	40.21	15.38	16.94	14.58
Participated in voluntary labor^	0.2871	0.1893	0.2139	0.45	0.39	0.41
Work in agricultural sector ^	0.3395	0.3363	0.2642	0.47	0.47	0.44
Currently married^	0.6615	0.6839	0.747	0.47	0.46	0.43
Currently in school^	0.1096	0.09717	0.0817	0.31	0.3	0.27
Participated in arisan^	0.3814	0.3920	0.3241	0.49	0.49	0.47
Amount contributed at each arisan meeting	0.0369	0.0608	0.0935	0.095	0.15	0.22

Note: All monetary values are in expressed in real million Rupiah (year 2007 is the base year).

^Dummy variables

Table 3.4: Exposure of IFLS Households to Natural Hazards

	% of Households affected			% of Districts affected		
	1997/1998	2000	2007/2008	1997/1998	2000	2007/2008
Hazards						
Any	2.14	15.16	78.95	13.33	13.02	74.45
Earthquakes	0.74	1.04	5.57	8.33	0.47	5.29
Floods	0.86	0.00	69.04	8.33	0	63.88
Landslides	0.27	12.36	22.58	1.67	10.23	23.35
Floods and landslides	0.00	0.00	8.71	0	0	11.01
Storms	0.25	2.68	33.83	1.11	2.33	32.16
Surge	0.00	0.00	5.58	0	0	6.61
Total number of households	6716	8654	10991	-	-	-
Total number of districts	-	-	-	180	215	227

Source: Author's calculation using the matched sample of Indonesian Family Life Survey and BNPB disaster database (http://www.bnpb.go.id).

Table 3.5: Prediction of the Number of Disasters Based on Historic Exposure

	(1)	(2)
VARIABLES	All disasters	
		(with Kiviet correction)
Lagged variables (last year)		
# of disasters	0.350***	0.640***
	(0.0124)	(0.0100)
Constant	-0.149	-0.228***
	(0.197)	(0.0133)
District fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	7311	7311
R-squared	0.450	0.270

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6: Impact of Expected and Unexpected Number of Disasters on Female Market Labor

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1st stage		1st stage		1st stage	
	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked
Realized number of disasters	0.157	0.0503				
	(0.208)	(0.0378)				
Unexpected number of disasters	-0.248	-0.0814**	-0.0896	-0.0299*	-0.102	-0.0334**
	(0.202)	(0.0376)	(0.0799)	(0.0166)	(0.0774)	(0.0164)
Expected number of disasters			0.190	0.0523		
			(0.191)	(0.0377)		
Sector-gender-province-year wage (instrument)	1.508***		1.453***		1.447***	
	(0.348)		(0.344)		(0.343)	
Log weekly wage (instrumented)		0.0338		0.0374		0.0360
		(0.0322)		(0.0333)		(0.0335)
Average weekly wage of male household members	0.0787*	-0.00473	0.0786*	-0.00478	0.0796*	-0.00448
	(0.0456)	(0.00790)	(0.0458)	(0.00791)	(0.0458)	(0.00794)
Age	0.282***	0.0419***	0.284***	0.0409***	0.282***	0.0405***
	(0.0609)	(0.0143)	(0.0626)	(0.0146)	(0.0626)	(0.0146)
Age squared	-0.00316***	-0.000465***	-0.00320***	-0.000452**	-0.00317***	-0.000448**
	(0.000789)	(0.000173)	(0.000812)	(0.000176)	(0.000812)	(0.000176)
Works in agriculture (dummy)	-0.224	-0.00842	-0.184	-0.0109	-0.170	-0.00799
	(0.317)	(0.0523)	(0.302)	(0.0523)	(0.301)	(0.0521)
Constant	-12.38***	2.478***	-11.31***	2.532***	-11.56***	2.459***
	(4.341)	(0.293)	(4.348)	(0.306)	(4.321)	(0.299)
Chi squared statistic of testing:						
Instrument = 0	18.79***	-	17.88***	-	17.82***	-
Unpeected = expected	-	-	-	4.69**	-	-
Expected number of disasters = 0	-	-	-	1.92	-	-
Unexpected number of disasters = 0	-	4.69**	-	3.24*	-	4.15**
Observations	1,727	1,558	1,727	1,558	1,727	1,558

Note: Clustered (household level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include district (kabupaten), household, and year fixed effects.

Table 3.7: Impact of Expected and Unexpected Number of Disasters on Male Market Labor

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1st stage		1st stage		1st stage	
	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked
Realized number of disasters	-0.0228	0.0548*				
	(0.135)	(0.0321)				
Unexpected number of disasters	-0.0746	-0.0441	-0.0973*	0.0107	-0.0955*	0.00589
	(0.130)	(0.0311)	(0.0529)	(0.0148)	(0.0509)	(0.0143)
Expected number of disasters			-0.0228	0.0548*		
			(0.135)	(0.0321)		
Sector-gender-province-year wage (instrument)	1.904***		1.904***		1.906***	
	(0.323)		(0.323)		(0.322)	
Log weekly wage (instrumented)		-0.0112		-0.0112		-0.0133
		(0.0270)		(0.0270)		(0.0271)
Average weekly wage of female household members	0.0297	0.000636	0.0297	0.000636	0.0296	0.000798
	(0.0206)	(0.00420)	(0.0206)	(0.00420)	(0.0206)	(0.00418)
Age	0.290***	0.0361***	0.290***	0.0361***	0.290***	0.0367***
	(0.0526)	(0.0137)	(0.0526)	(0.0137)	(0.0526)	(0.0137)
Age squared	-0.00357***	-0.000351**	-0.00357***	-0.000351**	-0.00357***	-0.000360**
	(0.000659)	(0.000165)	(0.000659)	(0.000165)	(0.000658)	(0.000165)
Works in agriculture (dummy)	0.0130	0.00161	0.0130	0.00161	0.0118	0.00548
	(0.232)	(0.0581)	(0.232)	(0.0581)	(0.232)	(0.0581)
Constant	-16.25***	2.509***	-16.29***	2.592***	-16.26***	2.512***
	(4.022)	(0.324)	(3.998)	(0.328)	(4.013)	(0.324)
Year fixed effects	yes	yes	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes	yes	yes
Household fixed effects	yes	yes	yes	yes	yes	yes
Chi squared statistic of testing:						
Instrument = 0	34.67***	-	34.67***	-	35.12***	-
Unpeected = expected	-	-	-	2.02	-	-
Expected number of disasters = 0	-	-	-	2.92*	-	-
Unexpected number of disasters = 0	-	2.02	-	0.52	-	0.17
Observations	**2,011**	1,992	2,011	1,992	2,011	1,992

Note: Clustered (household level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include district (kabupaten), household, and year fixed effects.

Table 3.8: Impact of Expected and Unexpected Number of Disasters on Voluntary Labor

	(1)		(2)		(3)		(4)		(5)		(6)	
VARIABLES	Voluntary Labor (dummy)											
	Women						Men					
		dy/dx		dy/dx		dy/dx		dy/dx		dy/dx		dy/dx
Realized number of disasters	-0.301***	-.0707575					-0.0206	-.005439				
	(0.0915)						(0.0557)					
Unexpected number of disasters	0.331***	.0778001	0.0299	.0070425	0.0352	.0083317	0.0116	.0030594	-0.00901	-.0023797	-0.00834	-.0022041
	(0.0944)		(0.0283)		(0.0282)		(0.0575)		(0.0202)		(0.0201)	
Expected number of disasters			-0.301***	-.0707575					-0.0206	-.005439		
			(0.0915)						(0.0557)			
Age	0.0110	.0025906	0.0110	.0025906	0.0130	.0030748	0.0961***	.0253715	0.0961***	.0253715	0.0960***	.0253552
	(0.0198)		(0.0198)		(0.0197)		(0.0164)		(0.0164)		(0.0164)	
Works in agriculture (dummy)	0.0942	.0221836	0.0942	.0221836	0.0925	.0218884	0.290***	.076611	0.290***	.076611	0.290***	.0764989
	(0.109)		(0.109)		(0.109)		(0.0776)		(0.0776)		(0.0775)	
Constant	-14.63		-14.63		-14.43		5.637		5.637		5.617	
	(146,443)		(145,569)		(163,144)		(3,501)		(3,501)		(3,295)	
Chi squared statistic of testing:												
Unpeected = expected			12.27***						0.04			
Expected number of disasters = 0			10.8***						0.14			
Unexpected number of disasters = 0	12.27***		1.12		1.56		0.04		0.20		0.17	
Observations	1,959		1,959		1,959		3,564		3,564		3,564	

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include district (kabupaten), household, and year fixed effects.

Table 3.9: Impact of Expected and Unexpected Number of Disasters on Household Borrowing

	(1)		(2)		(3)		(4)	(5)	(6)
VARIABLES	Borrowed money last year (dummy)						Log (amount borrowed)		
		dy/dx		dy/dx		dy/dx			
Realized number of disasters	0.0227	.0058804					0.0956		
	(0.0212)						(0.0706)		
Unexpected number of disasters	-6.78e-05	-.0000176	0.0226**	.0058602	0.0229**	.0059228	-0.0351	0.0605*	0.0644**
	(0.0235)		(0.00957)		(0.00958)		(0.0783)	(0.0329)	(0.0325)
Expected number of disasters			0.0225	.0058269				0.0952	
			(0.0212)					(0.0706)	
# of children under 5 years old	0.0799***	.0207004	0.0799***	.020697	0.0801***	.020742	0.284***	0.284***	0.284***
	(0.0228)		(0.0228)		(0.0229)		(0.0824)	(0.0824)	(0.0824)
# of children between 6 to 14 years old	0.132***	.0341172	0.132***	.0341169	0.132***	.0341527	0.488***	0.488***	0.489***
	(0.0170)		(0.0170)		(0.0170)		(0.0639)	(0.0639)	(0.0639)
Constant	-1.452***		-1.451***		-1.449***		0.670	0.670	0.682
	(0.149)		(0.149)		(0.149)		(0.478)	(0.478)	(0.479)
Chi squared statistic of testing:									
Unpeected = expected			0.00					2.20	
Expected number of disasters = 0			1.12					1.82	
Unexpected number of disasters = 0	0.00		5.59**		5.70**		0.20	3.38*	3.93**
Observations	8,009		8,009		8,009		7,973	7,973	7,973

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include district (kabupaten), household, and year fixed effects.

Table 3.10: Impact of Expected and Unexpected Number of Disasters on Participation in Arisan Meetings

	(1)		(2)		(3)		(4)	(5)	(6)
VARIABLES	Participation in arisan (dummy)						Total contribution in arisan meetings		
		dy/dx		dy/dx		dy/dx			
Realized number of disasters	-0.0590	-.0128629					0.0578		
	(0.0496)						(0.0741)		
Unexpected number of disasters	0.0909*	.0198366	0.0320*	.0069737	0.0345**	.0075452	-0.119	-0.0610**	-0.0628**
	(0.0506)		(0.0173)		(0.0172)		(0.0771)	(0.0244)	(0.0244)
Expected number of disasters			-0.0590	-.0128629				0.0578	
			(0.0496)					(0.0741)	
Male (dummy)	-1.182***	-.2578339	-1.182***	-.2578339	-1.177***	-.2574512	-0.0127	-0.0127	-0.0133
	(0.0722)		(0.0722)		(0.0715)		(0.0730)	(0.0730)	(0.0729)
Constant	-1.567		-1.567		-1.517		9.275***	9.275***	9.247***
	(1.126)		(1.126)		(1.120)		(0.601)	(0.601)	(0.594)
Chi squared statistic of testing:									
Unpeected = expected			3.22*					2.37	
Expected number of disasters = 0			1.41					0.61	
Unexpected number of disasters = 0	3.22*		3.4*		4.03**		2.37	6.24**	6.62**
Observations	7,046		7,046		7,046		1,963	1,963	1,963

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include district (kabupaten), household, and year fixed effects.

3.7 Appendix C

C.1 The Model

In this section, I develop a collective household model with shocks to labor supply from natural hazards. I follow closely the collective model in Chiappori, Fortin and Lacroix (2002) but also draw on Jayachandran (2006) and Browning and Gortz (2012). In our framework, the household consists of two individuals, one male and one female. Under the collective framework, the intrahousehold decision process always leads to Pareto-efficient outcomes.

C.2 Assumptions

Formally, let m_i and c_i, for $i = [m, f]$, denote, respectively, the male or female household member's market labor supply and consumption of a private Hicksian composite good. I set the price of the private good to unity, and each member receives a wage w_i for supplying labor on the market. The household also engages in the domestic production of food crops according to the production function $F(f_m, f_f) = f_m^{\beta} + f_f^{\eta}$, where f_i denotes member i's farm labor supply. Without loss of generality, I assume that domestic production uses only labor inputs. The parameters $\beta \in (0, 1)$ and $\eta \in (0, 1)$ represent the relative efficiencies of male and female labor in domestic production. Let q denote total domestic output, which is the sum of the male consumption of crops, q_m, female consumption of crops, q_f, and cash crops, q_a, to be sold on the market for a price P. I focus on the allocation of labor in domestic production and labor on the market. Therefore, total labor supply, T, is exogenous and in the form $T \geq f_i + m_i$.

Household members have identical Stone-Geary preferences over private good and food crops consumption:

$$U_i(c_i, q_i) = log(c_i) + \frac{1+\gamma}{\gamma} log(q_i - \underline{q})$$

where $\gamma \in (0,1)$. Individuals must consume at least the subsistence level of crops $\underline{q} \geq 0$. I consider the general case of "caring" individuals (Becker 1991), that is, individuals whose preferences are represented by a utility function that depends on their own egotistic utility as well as their spouses'. Formally, member i's welfare function can be expressed in the form:

$$\Psi_i = U_i(c_i, q_i) + \lambda_i U_j(c_j, q_j)$$

where $i, j = [m, f]$ and $i \neq j$. Ψ_i is continuous, increasing, and quasi-concave in egotistic utilities U_i and U_j. $\lambda_i \in (0,1)$ describes the extent member i cares about member j's utility. I exclude the possibilities that member i dislikes her partner such that $\lambda_i < 0$ or member i cares more about her partner than herself such that $\lambda_i > 1$.

Taking a weighted average of each member's welfare function, I can express the household welfare function as :

$$\Psi_h = \theta \Psi_m + (1-\theta)\Psi_f = \nu U_m(c_m, q_m) + U_f(c_f, q_f)$$

where ν, the Pareto weight, is a composite function of λ_m, λ_f and the weight θ. The Pareto weight represents the relative weight of the male household member in the household decision process.

C.3 Household Maximization Problem

Let y denote the amount of non-labor income that the household receives. For any given (w_m, w_f, y, P), there exists a Pareto weight ν such that (c_i, q_i, m_i, f_i) solves the following household problem:

$$\max_{c_i, q_i, m_i, f_i} \nu U_m(c_m, q_m) + U_f(c_f, q_f)$$

subject to

$$c_m + c_f \leq P(F - q_m - q_f) + y + m_m w_m + m_f w_f$$

$$m_f \leq \overline{m},$$

$$f_i + m_i \leq T,$$

where the constraint $m_f \leq \overline{m}$ represents an upper limit on a woman's market hours of work in the presence of natural hazards. This constraint reflects social norms that deem women more vulnerable to work outside of the home after disasters. In addition, anthropological evidence suggests that Indonesian women assume the roles of caretakers for children and the elderly in times of shocks, for example, after the 2004 Tsunami (Hellwig and Tagliacozzo 2009). Thus, this constraint allows us to consider the possibility that women who experience natural disasters may find her optimal market labor supply, m_f^*, being restricted to a sub-optimal level, $\overline{m}$.

C.4 Optimality Conditions

The first order conditions (FOCs) are summarized in Appendix D. They imply different conditions on farm and market labor supply between men and women. With and without natural disasters, the following condition holds for male household members:

$$w_m = PF_f^m$$

where F_f^m is the marginal product of male farm labor. The intuition here is that the wage of male market labor is equal to the wage of male farm labor. By the assumption of the model, natural disasters have no impact on the marginal productivity of male labor on the farm.

For female members, I derive the following condition from the FOCs:

$$PF_f^f = \begin{cases} w_f & \text{if } d = 0, \\ w_f - \frac{\alpha_2}{U_c^f} & \text{if } d = 1. \end{cases}$$

where $d = [0, 1]$ is an indicator function of the occurrence of natural disasters. The left-hand-side of the condition represents the wage of female farm labor and is analogous to that in the male labor condition. Under the no-disaster scenario, $d = 0$, the farm wage is equal to the market wage of female labor. Under the disaster scenario, $d = 1$, the farm wage is equal to the market wage of female labor plus the term $-\frac{\alpha_2}{U_c^f}$ if and only if the constraint $m_f \leq \overline{m}$ is binding. In other words, if the optimal level of female market labor supply is restricted to a sub-optimal level, $\overline{m}$, such that $m_f^* = \overline{m}$, then $\alpha_2 > 0$ and $PF_f^f = w_f - \frac{\alpha_2}{U_c^f}$ holds.

The intuition here is that for any given (w_f, P) and when $\alpha_2 > 0$,

$$F_f^f(d=1) < F_f^f(d=0).$$

Hence, for a given level of domestic output, $f_f(d=1) > f_f(d=0)$. Since $f_f + m_f \leq T$, this increase in female labor on the farm reflects a reduction in market labor supply under the disaster scenario. This result provides a testable condition on female market labor supply in the empirical analysis.

C.5 Theoretical Results

Relationship between Market Labor Supply and Wage

Appendix E gives the optimal expressions for farm and market labor supply. Taking comparative statics of labor supply with respect to wages, I arrive at the following implications. First, the theory implies a substitution effect as $\partial m_m^*/\partial w_m^* > 0$. When the male market wage increases, the theory predicts an increase in the male market labor supply as he substitutes time away from leisure. Similarly, the theory predicts a substitution effect for female household members via $\partial m_f^*/\partial w_f^* > 0$.[11]

By our assumption, natural disasters only impact the model through its effect on limiting women's market labor supply. Thus, the relationship between wage and market labor supply remains unchanged for men with and without disasters.

Under the no-disaster scenario, the expression between female market labor supply and female wage is in the form:

[11] I consider the effects of each partner's wage on the other partner's labor supply in a later extension of the model.

$$\frac{\partial m_f^*(d=0)}{\partial w_f^*} = -\frac{1}{\eta - 1}\frac{1}{P\eta}[w_f \frac{1}{P\eta}]^{\frac{1}{\eta-1}-1} > 0$$

This relationship only depends on the relative efficiencies of male and female farm labor in domestic food crops production, the price of cash crops, and the market wage for female.

Under the disaster scenario, the equivalent expression is in the form:

$$\frac{\partial m_f^*(d=1)}{\partial w_f^*} = -\frac{1}{\eta - 1}\frac{1}{P\eta}[(w_f - \frac{\alpha_2}{U_c^f})\frac{1}{P\eta}]^{\frac{1}{\eta-1}-1} > 0$$

Here, the relationship depends not only on a given (w_f, η, β, P), but also her marginal utility of private goods consumption and α_2, the Lagrange multiplier of the time allocation constraint. Since $\eta \in (0,1)$ and $\alpha_2 \in (0,1)$, I can see that $\partial m_f^*(d=1)/\partial w_f^* > \partial m_f^*(d=0)/\partial w_f^*$. In other words, when the time allocation constraint on women's labor supply is binding due to natural disasters, women's market labor supply becomes more responsive to changes in wages at every wage level. Figure 1 depicts this change in the wage and labor supply relationship.This implication provides a testable hypothesis in the behavior of Indonesian women's labor supply in the empirical analysis.

Elasticity of Labor Supply

Let ζ_i denote the elasticity of member i's market labor with respect to her market wage:

$$\zeta_i = \frac{\partial m_i^*}{\partial w_i^*} \cdot \frac{w_i^*}{m_i^*}$$

On one hand, the elasticity of male market labor with respect to his wage, ζ_m, is identical under both disaster and no-disaster scenarios. On the other hand, since I know for female household members that for a given (w_f^*, P, η), $\partial m_f^*(d=1)/\partial w_f^* > \partial m_f^*(d=0)/\partial w_f^*$. Thus, any remaining difference between $\zeta_f(d=1)$ and $\zeta_f(d=0)$ depends on $m_f^*(d=0)$ and $m_f^*(d=1)$.

In the no-disaster scenario, I can express the optimal female labor supply on the market as:

$$m_f^*(d=0) = T - [w_f \frac{1}{P\eta}]^{\frac{1}{\eta-1}}$$

In the disaster scenario and when the time allocation constraint is binding, optimal female labor supply can be expressed as:

$$m_f^*(d=1) = T - [(w_f - \frac{\alpha_2}{U_c^f})\frac{1}{P\eta}]^{\frac{1}{\eta-1}}$$

Here, I can see that $m_f^*(d=1) < m_f^*(d=0)$. Thus, for a given (w_f^*, P, η), I can conclude that $w_f^*/m_f^*(d=1) > w_f^*/m_f^*(d=0)$. Hence, in the presence of natural disasters and when the time allocation constraint on women's market labor supply is binding, that is, when $\alpha_2 > 0$, the elasticity of female market labor with respect to market wage increases such that $\zeta_f(d=1) > \zeta_f(d=0)$.

3.8 Appendix D

First Order Conditions

$$
\begin{aligned}
\mathcal{L} &= \nu U_m(c_m, q_m) + U_f(c_f, q_f) \\
&+ \alpha_1[P(F - q_m - q_f) + y + m_m w_m + m_f w_f - [c_m + c_f] \\
&+ \alpha_2[\overline{m} - m_f] \\
&+ \alpha_3[T - f_m - m_m] \\
&+ \alpha_4[T - f_f - m_f]
\end{aligned}
\tag{3.13}
$$

$$\frac{\partial \mathcal{L}}{\partial c_m} : \alpha_1 = \nu \frac{\partial U_m}{\partial c_m} \tag{3.14}$$

$$\frac{\partial \mathcal{L}}{\partial c_f} : \alpha_1 = \frac{\partial U_f}{\partial c_f} \tag{3.15}$$

$$\frac{\partial \mathcal{L}}{\partial q_m} : \alpha_1 P = \nu \frac{\partial U_m}{\partial q_m} \tag{3.16}$$

$$\frac{\partial \mathcal{L}}{\partial q_f} : \alpha_1 P = \frac{\partial U_f}{\partial q_f} \tag{3.17}$$

(3.14) and (3.15) $\implies \frac{U_c^f}{U_c^m} = \nu$

(3.14) and (3.16) $\implies U_q^m = U_c^m P$

(3.15) and (3.17) $\implies U_q^f = U_c^f P$

$$\frac{\partial \mathcal{L}}{\partial f_m} : \alpha_3 = \alpha_1 P \frac{\partial F}{\partial f_m} \tag{3.18}$$

$$\frac{\partial \mathcal{L}}{\partial f_f} : \alpha_4 = \alpha_1 P \frac{\partial F}{\partial f_f} \tag{3.19}$$

$$\frac{\partial \mathcal{L}}{\partial m_m} : \alpha_3 = \alpha_1 w_m \tag{3.20}$$

$$\frac{\partial \mathcal{L}}{\partial m_f} : \alpha_2 + \alpha_4 = \alpha_1 w_f \tag{3.21}$$

3.9 Appendix E

Labor Supply

The interior solution to the maximization problem gives the following expressions for farm and market labor supply:

$$f_m^* = (\frac{w_m}{P\beta})^{\frac{1}{\beta-1}}$$

$$f_f^* = [(w_f - \frac{\alpha_2}{U_c^f})\frac{1}{P\eta}]^{\frac{1}{\eta-1}}$$

$$m_m^* = T - f_m^* = T - (\frac{w_m}{P\beta})^{\frac{1}{\beta-1}}$$

$$m_f^* = T - f_f^* = T - [(w_f - \frac{\alpha_2}{U_c^f})\frac{1}{P\eta}]^{\frac{1}{\eta-1}}$$

3.10 Appendix F

Table 3.11: Impact of Earthquake and Flood Magnitude on Female Market Labor (Objective Measure)

	(1)	(2)
VARIABLES	Women	
	1st stage	
	Log weekly wage	Log of yearly weeks worked
Earthquake magnitude	0.145	-0.0365**
	(0.0967)	(0.0162)
Flood magnitude	-0.0823	-0.0134
	(0.0737)	(0.0158)
Sector-gender-province-year wage (instrument)	1.645***	
	(0.348)	
Log weekly wage (instrumented)		0.0339
		(0.0308)
Average weekly wage of male household members	0.0803*	-0.00441
	(0.0461)	(0.00793)
Age	0.285***	0.0404***
	(0.0605)	(0.0142)
Age squared	-0.00319***	-0.000446***
	(0.000783)	(0.000172)
Works in agriculture (dummy)	-0.205	-0.00344
	(0.315)	(0.0522)
Constant	-14.16***	2.494***
	(4.338)	(0.289)
Chi squared statistic of testing:		
Instrument = 0	22.32***	-
Earthquake = Flood	-	1.17
Earthquake = 0	-	5.10**
Flood = 0	-	0.71
Observations	1,727	1,558

Note: Clustered (household level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All specifications include district (kabupaten), household, and year fixed effects.

Table 3.12: Impact of Earthquake and Flood Magnitude on Male Market Labor (Objective Measure)

	(1)	(2)
VARIABLES	Men	
	1st stage	
	Log weekly wage	Log of yearly weeks worked
Earthquake magnitude	-0.0454	0.0361**
	(0.0480)	(0.0178)
Flood magnitude	-0.0135	0.00672
	(0.0515)	(0.0135)
Sector-gender-province-year wage (instrument)	1.886***	
	(0.321)	
Log weekly wage (instrumented)		-0.0121
		(0.0276)
Average weekly wage of female household members	0.0291	0.000731
	(0.0205)	(0.00418)
Age	0.295***	0.0368***
	(0.0532)	(0.0138)
Age squared	-0.00362***	-0.000361**
	(0.000667)	(0.000167)
Works in agriculture (dummy)	0.0163	0.00853
	(0.235)	(0.0576)
Constant	-16.16***	2.478***
	(4.020)	(0.323)
Chi squared statistic of testing:		
Instrument = 0	34.5***	-
Earthquake = Flood	-	1.86
Earthquake = 0	-	4.09**
Flood = 0	-	0.25
Observations	2,011	1,992

Note: Clustered (household level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All specifications include district (kabupaten), household, and year fixed effects.

Table 3.13: Impact of Earthquake and Flood Magnitude on Voluntary Labor (Objective Measure)

	(1)		(2)	
VARIABLES	Voluntary Labor (dummy)			
	Women		Men	
		dy/dx		dy/dx
Earthquake magnitude	0.0652*	0.0150	0.0942***	0.0257
	(0.0390)		(0.0276)	
Flood magnitude	0.0657**	0.0151	-0.102***	-0.0279
	(0.0303)		(0.0249)	
Age	-0.00241	-0/000553	0.0861***	0.0235
	(0.0215)		(0.0208)	
# of children under 5 years old	-0.117*	-0.0268	0.0271	0.00739
	(0.0604)		(0.0450)	
# of children between 6 to 14 years old	0.0135	0.00310	-0.0619*	-0.0169
	(0.0437)		(0.0349)	
Works in agriculture (dummy)	-0.0479	-0.0110	-0.234**	-0.0638
	(0.103)		(0.0926)	
Constant	0.0369		0.160	
	-13.37		6.265	
	(66,797)		(2,724)	
Chi squared statistic of testing:				
Earthquake = Flood	0.00	-	26.71***	-
Earthquake = 0	2.8*	-	13.51***	-
Flood = 0	4.71**	-	16.05***	-
Observations	2,085	-	3,164	-

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

All specifications include district (kabupaten), household, and year fixed effects.

Table 3.14: Impact of Earthquake and Flood Magnitude on Household Borrowing and Arisan Participation

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Household borrowed money last year (dummy)		Log (amount borrowed)	Participation in arisan (dummy)		Total arisan contribution
		dy/dx			dy/dx	
Earthquake magnitude	-0.0271	-0.00798	-0.118*	0.0229	0.00584	-0.0145
	(0.0175)		(0.0687)	(0.0158)		(0.0253)
Flood magnitude	-0.0154	-0.00454	-0.0584	0.00943	0.00240	-0.0128
	(0.0125)		(0.0491)	(0.0127)		(0.0174)
# of children under 5 years old	0.126***	0.0370	0.530***	0.00422	0.00108	-0.0262
	(0.0347)		(0.147)	(0.0266)		(0.0363)
# of children between 6 to 14 years old	0.139***	0.0408	0.614***	0.0390**	0.00994	-0.00918
	(0.0258)		(0.113)	(0.0197)		(0.0281)
Female unpaid labor in household (dummy)	0.374***	0.110	1.726***			
	(0.121)		(0.579)			
Male (dummy)				-1.152***	-0.293	-0.0792
				(0.0591)		(0.0665)
Age				0.0116***	0.00295	-0.00217
				(0.00185)		(0.00250)
Works in agriculture (dummy)	0.0412	0.0121	0.326	0.0797	0.0203	0.105
	(0.0658)		(0.271)	(0.0509)		(0.0684)
Constant	-1.872***		-1.522*	-4.274***		9.770***
	(0.246)		(0.890)	(1.331)		(0.539)
Chi squared statistic of testing:						
Earthquake = Flood	0.30	-	0.48	0.45	-	0.00
Earthquake = 0	2.40	-	2.95*	2.11	-	0.33
Flood = 0	1.51	-	1.41	0.55	-	0.54
Observations	4,462	-	4,433	10,387	-	3,258

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include district, household, and year fixed effects.

Table 3.15: Impact of Expected and Unexpected Number of Disasters on Female Market Labor (District-Level Clustering)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1st stage		1st stage		1st stage	
	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked
Realized number of disasters	0.159	0.0362				
	(0.189)	(0.0260)				
Unexpected number of disasters	-0.174	-0.0613**	-0.00839	-0.0241**	-0.0165	-0.0262**
	(0.194)	(0.0281)	(0.0669)	(0.0118)	(0.0692)	(0.0131)
Expected number of disasters			0.238	0.0452		
			(0.226)	(0.0295)		
Sector-gender-province-year wage (instrument)	1.508***		1.512***		1.490***	
	(0.327)		(0.327)		(0.324)	
Log weekly wage (instrumented)		0.0652**		0.0652**		0.0652**
		(0.0305)		(0.0305)		(0.0303)
Average weekly wage of male household members	0.125***	-0.00757	0.125***	-0.00759	0.128***	-0.00757
	(0.0379)	(0.00763)	(0.0380)	(0.00763)	(0.0383)	(0.00760)
Age	0.282***	0.0347**	0.282***	0.0348**	0.281***	0.0345**
	(0.0647)	(0.0139)	(0.0648)	(0.0140)	(0.0646)	(0.0140)
Age squared	-0.00319***	-0.000375**	-0.00320***	-0.000377**	-0.00318***	-0.000372**
	(0.000842)	(0.000171)	(0.000843)	(0.000171)	(0.000840)	(0.000171)
Works in agriculture (dummy)	-0.259	-0.0149	-0.267	-0.0156	-0.249	-0.0138
	(0.280)	(0.0477)	(0.279)	(0.0477)	(0.281)	(0.0477)
Constant	-12.43***	2.217***	-12.08***	2.288***	-12.25***	2.215***
	(3.880)	(0.373)	(3.872)	(0.382)	(3.861)	(0.370)
Chi squared statistic of testing:						
Instrument = 0	21.25***	-	21.34***	-	21.08***	-
Unpeected = expected	-	-	-	5.43**	-	-
Expected number of disasters = 0	-	-	-	2.36	-	-
Unexpected number of disasters = 0	-	4.76**	-	4.14*	-	4.04**
Observations	1,727	1,558	1,727	1,558	1,727	1,558

Note: Clustered (kabupaten level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include household and year fixed effects.

Table 3.16: Impact of Expected and Unexpected Number of Disasters on Male Market Labor (District-Level Clustering)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1st stage		1st stage		1st stage	
	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked	Log weekly wage	Log of yearly weeks worked
Realized number of disasters	0.0771	0.0142				
	(0.0627)	(0.0124)				
Unexpected number of disasters	-0.122	-0.0185	-0.0420	-0.00379	-0.0406	-0.00347
	(0.0772)	(0.0148)	(0.0288)	(0.00786)	(0.0285)	(0.00803)
Expected number of disasters			0.0613	0.0250*		
			(0.0749)	(0.0132)		
Sector-gender-province-year wage (instrument)	1.854***		1.856***		1.851***	
	(0.294)		(0.294)		(0.293)	
Log weekly wage (instrumented)		-0.0307		-0.0298		-0.0320
		(0.0268)		(0.0267)		(0.0271)
Average weekly wage of female household members	0.0362*	0.00146	0.0364*	0.00136	0.0370*	0.00164
	(0.0198)	(0.00476)	(0.0199)	(0.00478)	(0.0197)	(0.00477)
Age	0.304***	0.0425***	0.304***	0.0423***	0.304***	0.0429***
	(0.0516)	(0.0127)	(0.0515)	(0.0127)	(0.0514)	(0.0127)
Age squared	-0.00371***	-0.000424***	-0.00372***	-0.000421***	-0.00372***	-0.000429***
	(0.000634)	(0.000152)	(0.000633)	(0.000152)	(0.000632)	(0.000153)
Works in agriculture (dummy)	-0.197	-0.0540	-0.196	-0.0544	-0.193	-0.0543
	(0.241)	(0.0586)	(0.241)	(0.0586)	(0.241)	(0.0588)
Constant	-16.17***	2.642***	-16.08***	2.679***	-16.14***	2.653***
	(3.502)	(0.289)	(3.487)	(0.291)	(3.487)	(0.291)
Year fixed effects	yes	yes	yes	yes	yes	yes
Household fixed effects	yes	yes	yes	yes	yes	yes
Chi squared statistic of testing:						
Instrument = 0	39.84***	-	39.78***	-	39.88***	-
Unpeected = expected	-	-	-	3.83*	-	-
Expected number of disasters = 0	-	-	-	3.56*	-	-
Unexpected number of disasters = 0	-	1.57	-	0.23	-	0.19
Observations	**2,011**	1,992	2,011	1,992	2,011	1,992

Note: Clustered (kabupaten level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include household, and year fixed effects.

Table 3.17: Impact of Earthquake and Flood Magnitude on Female Market Labor (District-Level Clustering)

	(1)	(2)
VARIABLES	Women	
	1st stage Log weekly wage	Log of yearly weeks worked
Earthquake magnitude	0.108	-0.0292**
	(0.0785)	(0.0119)
Flood magnitude	-0.0286	-0.00344
	(0.0730)	(0.0121)
Sector-gender-province-year wage (instrument)	1.558***	
	(0.320)	
Log weekly wage (instrumented)		0.0642**
		(0.0289)
Average weekly wage of male household members	0.132***	-0.00772
	(0.0385)	(0.00754)
Age	0.284***	0.0345**
	(0.0647)	(0.0136)
Age squared	-0.00324***	-0.000372**
	(0.000842)	(0.000167)
Works in agriculture (dummy)	-0.265	-0.00846
	(0.283)	(0.0476)
Constant	-12.98***	2.226***
	(3.816)	(0.369)
Chi squared statistic of testing:		
Instrument = 0	23.68***	-
Earthquake = Flood	-	2.57
Earthquake = 0	-	6.03**
Flood = 0	-	0.08
Observations	1,727	1,558

Note: Clustered (kabupaten level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All specifications include household and year fixed effects.

Table 3.18: Impact of Earthquake and Flood Magnitude on Male Market Labor (District-Level Clustering)

	(1)	(2)
VARIABLES	Men	
	1st stage Log weekly wage	Log of yearly weeks worked
Earthquake magnitude	-0.0215	0.00982
	(0.0370)	(0.00720)
Flood magnitude	0.0343	-0.00632
	(0.0399)	(0.00763)
Sector-gender-province-year wage (instrument)	1.809***	
	(0.287)	
Log weekly wage (instrumented)		-0.0267
		(0.0274)
Average weekly wage of female household members	0.0378*	0.00133
	(0.0201)	(0.00478)
Age	0.306***	0.0414***
	(0.0514)	(0.0128)
Age squared	-0.00376***	-0.000411***
	(0.000632)	(0.000154)
Works in agriculture (dummy)	-0.190	-0.0529
	(0.244)	(0.0592)
Constant	-15.62***	2.621***
	(3.409)	(0.289)
Chi squared statistic of testing:		
Instrument = 0	39.71***	-
Earthquake = Flood	-	2.46
Earthquake = 0	-	1.86**
Flood = 0	-	0.69
Observations	2,011	1,992

Note: Clustered (kabupaten level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All specifications include household and year fixed effects.

Chapter 4: Natural Disasters and Vulnerability: Evidence from the 1997 Forest Fires

4.1 Introduction

Natural disasters have led to enormous economic and human losses in the last two decades. In particular, catastrophes such as the December 2004 tsunami in the Indian Ocean, the October 2005 earthquake in Pakistan, the September 2005 hurricane and inundation of New Orleans, the May 2008 earthquake in China and cyclone in Myanmar, and the February 2011 earthquake in New Zealand have called public attention to the enormous human and monetary costs of natural hazards.

While all human beings are vulnerable to natural disasters, the poor seem to be affected most. Indeed, 90% of disaster victims worldwide live in developing countries, where poverty and population pressures compel poor people to live on flood plains, in earthquake-prone zones, and on unstable hillsides (Annan 1999). Moreover, rural households often lack insurance against such risks. However, poor households are not necessarily vulnerable. For example, a household with very low but stable expected consumption may be poor, but another household with a higher expected consumption and greater risks is arguably more vulnerable. As such, targeting households that are both poor and vulnerable is fundamental to poverty reduction strategies (World Bank 2000).

The goal of this research is to investigate the link between households' poverty and vulnerability resulting from natural disasters, where "vulnerability" refers to reductions in the distribution of household consumption. By combining two waves of survey data from Indonesia, this chapter estimates and analyzes the role that a costly natural disaster plays in contributing to households' vulnerability, controlling for household characteristics which are themselves important determinants of vulnerability. Since natural disasters have an observable and adverse impact on macroeconomies in the short-run (Noy 2009), we consider the 1997 forest fires as an aggregate risk that affects households in the same way and we hypothesize that households who are more affected by the smoke from the fires are more vulnerable. While we are agnostic about the specific vehicle by which smoke affects households' vulnerability, possibilities include loss of income due to respiratory illness associated with suspended air particulates, business closures, and reductions in social services either because financial resources are re-allocated to combating the fires or because institutions close as a result of the smoke.

The analysis proceeds in two parts. First, we apply Ligon and Schechter (2003)'s utility measure of vulnerability to the Indonesian panel data to estimate and decompose vulnerability into its distinct sources. Specifically, vulnerability of the population is calculated by summing vulnerability across households. Second, we use an Ordinary Least Squares (OLS) regression model to examine the relationship between household characteristics and vulnerability in total and food consumption.

We find that households who earn more off-farm income and are headed by more educated individuals are less vulnerable, meaning that their total expenditures and food expenditures are less affected by natural disasters than households without off-farm income. Surprisingly, we also find that households who experienced some form of exogenous shocks, such as the death or the loss of employment of a household member, also face less vulnerability. This result suggests that these households have lower vulnerability, perhaps because they lost economically unproductive members. We also find that the 1997 forest fires affect households' vulnerability in total consumption but not in food consumption. Moreover, we find that the forest fires do not contribute to vulnerability as an aggregate risk.

The rest of the chapter is organized as follows: Section 4.2 presents a summary of the economic, sociological and disaster management literature on the topic of vulnerability. Section 4.3 provides a detailed description of the 1997 forest fires in Indonesia. Section 4.4 presents the empirical strategy used to estimate vulnerability in the context of Indonesia's forest fires. Section 4.5 presents an overview of the data. Section 4.6 presents the results of the econometric estimations, and Section 4.7 concludes and discusses the findings, policy implications, limitations and possible extensions of this study.

4.2 Estimating Vulnerability in Developing Countries

In general, "vulnerability" refers to the possibility that a negative outcome would move a household into poverty and force household members to reduce current consumption to smooth consumption in the long run. For example, Pritchett, et al. (2000) define vulnerability as the risk that a household will fall into poverty at least once in the next few years. In this case, vulnerability is forward-looking and is measured as a probability. Alternatively, Amin et al. (2003) estimate a baseline vulnerability measure for households based on a model of risk-sharing that assumes household consumption moves only with aggregate consumption and not with household income (Deaton 1997).

This literature tends to focus on macroeconomic risks such as a collapse in food production (e.g., Maxwell, et.al. 2000). Thus, the term "vulnerability" is used to describe a state of "food insecurity"[1] and the outcome of interest is the proportion of the total household budget spent on food. Significant effort has been devoted to predicting this outcome, employing measures such as rainfall patterns, forest cover, and soil productivity to spatially identify areas that are vulnerable to crop failures and food insecurity (e.g., Carter and May 1999).

In contrast, the disaster management literature has attempted to estimate vulnerability with respect to natural disasters as a particular source of risk. For example, Kreimer and Arnold (2000) start from the premise that people, households, and communities are vulnerable to damage from natural disasters. Consequently, their work defines vulnerability as an underlying condition distinct from the risky events that may trigger a disaster (e.g., Webb 1993). In other words, even if triggers of natural disasters occur, household and social systems either enable or inhibit

[1]Barrett (1999), for instance, defines food insecurity as "the risk of irreversible physical or mental impairment due to insufficient intake of macronutrients or micronutrients."

disasters through their responses. For example, Wisner et al. (1994) define vulnerability as the "characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a natural disaster."

This chapter adopts Ligon and Schechter (2003)'s measure of vulnerability, defined as the difference between the household's utility of expected consumption (i.e., consuming some particular bundle with certainty) and its expected utility of consumption. While many measures of vulnerability rely on the expected value of Foster-Greer-Thorbecke poverty measures, thus tending to assign too much risk to poor households, Ligon and Schechter's measure adopts a utility framework to capture the effects of risk on household welfare. This measure is advantageous to our study because vulnerability can be decomposed into distinct measures of poverty, measurement error, and exposures to aggregate risk, idiosyncratic risk, and unexplained risk. In this way, we can examine both the impact of household characteristics on household vulnerability in consumption and the impact on the decomposed measures of vulnerability.

4.3 The Indonesian Forest Fires

Indonesia has historically been a disaster-prone country, with at least 399 natural disasters recorded between 1907 and 2010 (Emergency Events Database 2011). Events ranging from cyclones, droughts, earthquakes, floods and forest fires have affected a total of nearly 28 million people. The nine recorded incidences of forest fires over the 87-year period of record have cost 300 lives and have caused over

US$9.3 billion in damages, the highest of all natural hazards that struck Indonesia.[2] Moreover, forest fires have far-reaching health consequences that are not limited to residents in the areas of burning. For instance, the 1997 fires in Indonesia produced visibility-limiting haze that caused traffic accidents and slowdowns, school and business closures, and increased incidence of respiratory health conditions. Moreover, easterly and southeasterly winds spread haze from the fires over an area far larger than where the fires occurred, adversely affecting people who did not initially live near the fires (Frankenberg et al. 2005). Prenatal exposure to smoke from the fires contributed to over 15,000 "missing children" across the country (Jayachandran 2009).

The 1997 forest fires were the largest in the country's history, burning some five million hectares of forests. The fires occurred on two major islands, Sumatra and Kalimantan, where population densities are low and considerable portions of the land area are covered by tropical rain forests. In many areas, however, the forest floor is covered with a flammable layer of dried organic material, which contributed to the islands' susceptibility to fires (Frankenberg et al. 2005).

In addition to ecological factors, the agricultural economies of Sumatra and Kalimantan also played a role in triggering the 1997 fires. Specifically, timber and plantation licenses that have been granted in recent years increased the quantity of land designated for commercial purposes, producing more flammable debris and fire used for clearing larger areas of land than does subsistence farming. In addition,

[2] For example, Emergency Events Database (2011) estimates the economic damage of the 1997 fires to Indonesia to be US$8 billion, greatly exceeding the US$4.5 billion economic damages to Indonesia stemming from the 2004 tsunami.

the Indonesian government's efforts to relieve densely-populated islands such as Java and Bali of population pressures by relocating residents to more rural areas increase the number of small-scale farmers who use fire to clear land (Ketterings et al. 1999). Further, fires have sometimes been used as a threat in land disputes (Glover and Jessup 1999). Each of these factors may have contributed to the large-scale forest fires that developed in the fall of 1997.

The forest fires were concentrated on the southern parts of Kalimantan and the eastern parts of Sumatra, leaving densely populated areas such as the island of Java unaffected. Nevertheless, Frankenberg et al. (2005) show that unlike the fire itself, the haze spread across nearby islands, spanning over 300 million square kilometers and potentially affecting tens of millions of people.

4.4 Empirical Specification

Indonesian households' vulnerability with respect to the 1997 forest fires is investigated in two parts. First, a utility model estimates the vulnerability of sampled households and decomposes the sources of vulnerability into four types of risks. Second, multivariate regression is used to determine the net effect of the 1997 forest fires on vulnerability after controlling for household characteristics. Each of the components of vulnerability is also regressed against the same household characteristics to provide a more nuanced analysis of the determinants of vulnerability.

4.4.1 The Utility Model

Ligon and Schechter (2003) propose a measure of vulnerability which can be decomposed into poverty, aggregate risk, idiosyncratic risk, and unexplained risk. Specifically, suppose that there exists a finite population of households $i = 1, 2, ..., n$; c^i denotes household i's consumption expenditures, which more directly and accurately determine household welfare than measures of income or wealth. To measure vulnerability, an arbitrary, strictly increasing, weakly concave function $U^i : R \rightarrow R$ mapping consumption expenditures onto the real line is chosen for each household, where $U^i(c) = (c^{1-\gamma})/(1-\gamma)$ for some parameter $\gamma > 0$. As γ [3] increases, the function U^i becomes increasingly concave, i.e., sensitive to risk (Friedman and Savage 1948). Given U^i, the vulnerability of the household with respect to consumption is thus defined as:

$$\begin{aligned} V^i(c) &= [U^i(z) - U^i(Ec^i)] \qquad && (Poverty) \\ &+ [U^i(Ec^i) - EU^i(c^i)] \qquad && (Risk) \end{aligned} \tag{4.1}$$

Here, z is some certainty-equivalent consumption level such that if household i's consumption is greater than or equal to z, the household is not regarded as vulnerable;[4] $U^i(z)$ is the utility of household i's consumption if they consume z

[3] In keeping with the estimates of this parameter in the literature and following Ligon and Schechter (2002), we set $\gamma = 2$.

[4] z is often interpreted as a poverty line. However, Ravallion and Bidani (1994) show that Indonesia's poverty profile is highly sensitive to small changes in the poverty line. In addition, Pradhan et al (2000) argue that while Indonesia's prevailing poverty line accurately reflects minimum subsistence income in some geographic areas, it over- or understates the amount of income needed in other areas. Hence, we set z equal to the average consumption of surveyed households.

and $U^i(Ec^i)$ is the utility of household i's expected consumption; and $EU^i(c^i)$ is household i's expected utility of consumption.

The first bracketed term measures poverty by calculating the difference between a concave function evaluated at z and at household i's expected consumption expenditures. The concavity of the function U^i implies that as Ec^i approaches the poverty line from below, an additional unit of expected consumption has diminishing marginal value in reducing poverty.

The second bracketed term measures the risk - uncertainties or contingencies that will affect the probabilities with which households obtain their expected level of consumption - faced by each household. In other words, it measures the difference between the household's utility of expected consumption and the expected utility of consumption. This difference is represented by the distance between points A and B in Figure 4.1. Consider two different scenarios. In the first scenario, each household faces two consumption periods. There exists a probability ρ that the household obtains the consumption bundle c_1 and a probability of $(1-\rho)$ that it obtains the bundle c_2 in both periods. The household's utility in this scenario can then be expressed as $EU(c)$, where

$$U\{c_1, c_2; \rho, (1-\rho)\} = \rho U(c_1) + (1-\rho)U(c_2) \tag{4.2}$$

In the second scenario, each household receives the consumption bundle $E(c)$ with certainty. The utility of the second scenario can then be expressed simply as $U(Ec)$. A risk-averse household would prefer to have consumption bundle $E(c)$ with certainty in both periods to having $EU(c)$ with uncertainty. Thus, the vertical distance between point A, or $U(Ec)$, and point B, or $EU(c)$, represents the risk that each household faces.

A possible third scenario is the certainty-equivalent allocation. In this case, each household would obtain consumption bundle z with certainty. The utility of this allocation is $U(z)$, represented by point E on the utility function. The distance between the points B and E represents poverty in the utility model if we consider z to be analogous to a poverty line.

Further, the risk measure in equation (4.1) can be decomposed into three distinct sources of risk: aggregate risks (risks that affect the entire economy such as changes in economy-wide wages or returns to capital that may, for example, be induced during a depression or a currency crisis), idiosyncratic risks (risks that are specific to the individual household such as the loss of employment of the household head or the sickness of a household member), and unexplained risks, which are analogous to the error, which is due to variation in unobserved factors and to measurement error in consumption. Thus, the above model is decomposable as follows:

$$\begin{aligned} V^i(c) = {} & [U^i(z) - U^i(Ec^i)] && (Poverty) \\ & + \{U^i(Ec^i_t) - EU^i[E(c^i_t|\bar{x}_t)]\} && (Aggregate\, Risk) \\ & + \{EU^i[E(c^i_t|\bar{x}_t)] - EU^i[E(c^i_t|\bar{x}_t, x^i_t)]\} && (Idiosyncractic\, Risk) \\ & + \{EU^i[E(c^i_t|\bar{x}_t, x^i_t)] - EU^i(c^i_t)\} && (Unexplained\, Risk\, \&\, Meas.\, Error) \end{aligned} \tag{4.3}$$

Here, c^i_t represents household i's consumption expenditures at time t; x^i_t represents its idiosyncratic variables; $\bar{x}_t$ is a vector of aggregate variables; and $E(c^i|\bar{x})$ denotes the expected level of consumption, c^i, conditional on a vector of aggregate variables, $\bar{x}$. Thus, the second bracketed term measures the aggregate risk faced by households, the third bracketed term measures idiosyncratic risk, and the fourth bracketed term measures unexplained risk.

Idiosyncratic risk can be attributed to the variation in k observed time-varying household characteristics $x_t^i = \{x_{1t}^i, ..., x_{kt}^i\}$ (see Appendix G). To examine the contribution of changes in specific variables to a household's idiosyncratic risk, we disaggregate idiosyncratic risk into three components: risk arising from variation in income, either from farm or non-farm labor; from changes in the amount of debt that the household owes at the time of the survey; and from exogenous shocks such as the death and/or the loss of employment of a household member in the past five years. Finally, to estimate the contributions of each type of risk to vulnerability in total consumption and food consumption, respectively, the magnitudes and statistical significance of each distinct source of vulnerability are compared. Estimates are obtained using Ligon and Schechter (2003)'s vulnerability routine in Stata in which consumption is estimated in levels.[5]

4.4.2 The Ordinary Least Squares Model

We estimate household vulnerability and further decompose it into the portion that comes from poverty, aggregate risk, idiosyncratic risk, and unexplained risk, re-

[5]We also estimated all models using logged values of consumption. The results are consistent with those presented here.

spectively. We then regress each element of vulnerability on a set of household characteristics. The general specification is:

$$
\begin{aligned}
Vulnerability = \beta_0 + \beta_1 Age + \beta_2 Male + \beta_3 Married + \beta_4 Primaryed \\
+ \beta_5 Secondaryed + \beta_6 Smoke + \beta_7 Farmbusp \\
+ \beta_8 Nfarmbusp + \beta_9 Credit + \beta_{10} Eshock + \epsilon
\end{aligned}
\tag{4.4}
$$

Here, Age is the age of the head of household; $Male$ is a dummy which equals 1 if the household is headed by a male and 0 if otherwise; $Married$ is a dummy which equals 1 if the head of household is married and 0 if otherwise; $Primaryed$ is a dummy which equals 1 if the head of household's highest level of education is primary school; $Secondaryed$ is a dummy which equals 1 if the head of household's highest level of education is secondary school; the omitted dummy variable is $Tertiaryed$, which equals 1 if the head of household's highest level of education is college or university; $Smoke$ measures smoke and other air pollutants at each enumeration point at the time that the survey was conducted; $Farmbusp$ is the income a household earns from providing farm labor in 1993; $Nfarmbusp$ is the initial income a household gains from off-farm labor in 1993; $Credit$ is the debt-total income ratio for each household at the time of the survey that functions as a proxy for its level of borrowing relative to its access to credit; and $Shock$ is a dummy which equals 1 if a household has experienced some form of exogenous shocks such as the death or loss of employment of a household member in the previous 5 years from 1997.

Equation (4.3) is estimated under 10 general specifications: Model I regresses household vulnerability in total consumption against a set of household characteristics, including $FarmHH$, a dummy which equals 1 if the household owns a farm business; Model II regresses the portion of vulnerability which comes from poverty against the same set of household characteristics; Model III focuses on the portion of vulnerability which comes from aggregate risk; Model IV investigates idiosyncratic risk; and Model V accounts for unexplained risk. Further, food insecurity, defined as the risk of serious physical or mental impairment due to insufficient intake of nutrients, is also likely to be affected by risk (Barrett 1999), whether aggregate, idiosyncratic, or unexplained. The proportion of a household's budget spent on food is thus an important indicator of an individual's livelihood (Maxwell et al. 2000). Thus, Models VI to X repeat the above estimations but focus instead on household vulnerability in food consumption. Since the effect of exposure to smoke on vulnerability may be different for households with different educational backgrounds,[6] the level of smoke at the time of survey enumeration is also interacted separately with education dummies in additional specifications.

4.5 Data Description

4.5.1 Data

The consumption data in this study come from the first and second waves of the Indonesian Family Life survey (IFLS), collected in 1993 and in 1997, respec-

[6] We thank an anonymous referee for bringing this possibility to our attention.

tively.[7] Conducted in 1993, the first wave of the IFLS is a socioeconomic and health survey based on a sample of households representing about 83% of the Indonesian population living in 13 of the nation's 26 provinces (Frankenberg and Karoly 1995). Among other topics, the survey gathered data on income, food expenditures, consumption expenditures, and community resources. The IFLS also surveyed health and education facilities in sampled communities. In total, it includes 7,224 households in 321 enumeration areas. The second wave, conducted at the end of 1997, revisited the same 321 enumeration areas, located the original households, and re-interviewed all household members. In cases in which survey respondents moved in the intervening years, interviews were conducted at the new locations provided that they lay within the 13 provinces enumerated in the first wave of the survey. Remarkably, over 94% of the households interviewed in the first wave were re-interviewed in IFLS2 (Frankenberg and Thomas 2000).

Smoke data are derived from the Total Ozone Mapping Spectrometer (TOMS) Aerosol Index maintained by NASA. These data have been used in a wide range of applications to understand the atmospheric movement of particles deriving from forest fires, desert dust storms, biomass burning, and other phenomena. This is the first instrument to track particles as they cross land/sea boundaries (TOMS 2011), which is crucial to understanding the spread of smoke in a nation comprised of over 17,500 islands.[8] Specifically, the TOMS data for Indonesia span the period from 3

[7]A potential shortcoming of our data lies in the fact that we have a 2-year panel whereas asymptotic results for vulnerability typically involve a large t (e.g., Ligon and Schechter (2003) use a 12-year panel). That being said, Ligon and Schechter (2004) use Monte Carlo simulations to demonstrate that their estimator of vulnerability (also employed in this analysis) performs better than static measures of poverty provided at least two rounds of panel data are available.

[8]See http://toms.gsfc.nasa.gov/aerosols/aerosols_v8.html for additional explanation of the

September to 16 November 1997. We thus match the average TOMS Aerosol Index for this period to the survey enumeration area in which the household resides to derive our measure of exposure to smoke.

It is important to note that the fires do not appear to have induced differential attrition among respondents who lived in areas affected by smoke from the forest fires. In fact, Frankenberg et al. (2005) point out that respondents in areas affected by smoke were as likely to die or to move in the three months preceding the IFLS interview date as respondents who lived in unaffected areas.

We aggregated individual-level data into households to form a panel. We then dropped households who reported having zero spending on both food and non-food consumption. The selection criteria yield samples of 7,141 in 1993 and 6,870 observations in 1997. After eliminating households that appear in only one of the two waves, the two datasets are appended to form a balanced panel of 13,512 observations.[9]

4.5.2 Summary Statistics

Table 4.1 presents descriptive statistics of the cross-sectional data in 1993 and 1997. Total consumption and food consumption were 1,309,856 Rupiah and 207,591 Rupiah in 1993 and 160,847 Rupiah and 158,419 Rupiah in 1997, respectively.[10] Frankenberg, Thomas, and Beegle (1999) note the same dramatic decline in expen-

TOMS data, including data assembly and definitions.

[9]The model was also estimated with an unbalanced panel, and the results are entirely consistent with those presented for the balanced panel.

[10]The exchange rate of the Indonesian Rupiah and US dollars during the time period 1st August, 1997 and 1st December, 1997 is 1IDR/0.00032US (average of the specified 123 days).

ditures, a reduction that they attribute to uncertainty associated with the Asian Financial Crisis, which represents both a form of aggregate risk because it induces economy-wide changes and a form of idiosyncratic risk because different households may be affected differently.[11] The dramatic reduction in average total consumption accompanied by the relatively moderate decline in food consumption suggests that food consumption expenditures are more resilient to shocks than non-food consumption.[12]

In both survey years, approximately 25% of households owned a farm business. Household income from farm and off-farm labor rose slightly between 1993 and 1997, with farm labor income averaging 874,262 Rupiah in 1997 and 500,015 Rupiah four years prior; and non-farm labor income averaging 1,819,491 Rupiah in 1997 and 1,361,474 Rupiah four years prior. Household debt in 1997 averaged 1,547,515 Rupiah, three times the level in 1993.

In terms of demographics, 76.9% and 81.8% of households were headed by males in 1993 and 1997, respectively. In 1997, 72.4% household heads were married; 71.1% of them had completed primary school as their highest level of education; 25.1% had graduated from secondary school, and only 3.8% have had tertiary education. The share of educational outcomes among these households was about the same in 1993. Only 10.1% of households in 1997 experienced some form of exogenous shocks as defined previously, while 30.5% of households experienced exogenous

[11] However, there is little reason to believe that the severity of those impacts should correlate with the intensity of smoke stemming from the fires. Hence, significant estimates of the impact of smoke should be independent of the financial crisis.

[12] Indeed, Frankenberg, Thomas, and Beegle (1999) report a 25% increase in the number of households falling below the poverty line between 1997 and 1998, noting that households seriously curtailed expenditures on education, health care, and other non-food forms of consumption.

shocks in 1993. Finally, on average, households live in areas with an aerosol index of 0.505, which Frankenberg et al. (2005) consider to be a "medium" level of exposure; however, the standard deviation of 0.76 underscores the high level of heterogeneity in smoke exposure. Differences in total consumption, food consumption, farm and off-farm income, and household debt are all statistically significant at the 1% level.

4.6 Results

Table 4.2 presents the estimates of vulnerability in total consumption and food consumption, respectively. Estimates of vulnerability are further decomposed into poverty, aggregate risk, idiosyncratic risk, and unexplained risk. To estimate the contributions of each type of risk to vulnerability, the magnitudes of the percentage shares of each distinct source in vulnerability are compared. Standard errors are bootstrapped with 10,000 repetitions.

Poverty is the largest component of vulnerability for both measures, representing 66.25% of vulnerability in total consumption and 48.81% of vulnerability in food consumption. Unexplained risk represents 24.21% of vulnerability in total consumption and 46.79% of vulnerability in food consumption. Interestingly, while aggregate risk accounts for 9.18% of vulnerability in total consumption and is the third largest component, it is the smallest facet of vulnerability in food consumption, representing only 1.21%. Given that vulnerability is defined as the sum of poverty, aggregate risk, idiosyncratic risk, and unexplained risk in this framework, we can infer from the differences in the estimates of vulnerability in total and food consumption that while aggregate risk accounts more for the vulnerability in non-food consumption, idiosyncratic risk explains to a greater extent household vulnerability in food consumption. Indeed, idiosyncratic risk explains about 3.15% of households' vulnerability in food consumption but just 0.11% in total consumption.

4.6.1 Vulnerability in Total Consumption

Table 4.3 presents the correlates between each element of vulnerability in total consumption on a set of fixed household characteristics. First, the relationship between households' exposure to smoke and aggregate risk is statistically zero, implying that households who live in areas that are more affected by smoke are no more likely to face aggregate risk than those living in areas less affected by smoke.[13] Nevertheless, for every 1-unit increase in the TOMS Aerosol Index, households face a 3.6% increase in vulnerability (significant at the 10% level). This increase in total vulnerability seems to come from the 7.37% increase in poverty (significant at the 1% level), implying that the 1997 forest fires affect some households' vulnerability via poverty instead of aggregate risk.

Meanwhile, the effect of household heads' education on households' vulnerability is ambiguous. While households with heads who graduated from primary schools are no more or less vulnerable than those with heads who graduated from universities, households with heads who graduated from secondary schools face 51.5% less vulnerability (significant at the 5% level) and 56.20% less poverty (significant at the

[13] A possible explanation is that aggregate risk is measured as the aggregate risk of the whole sample, not of the geographic subsamples.

5% level) than those with heads who graduated from universities. A possible explanation is that only 4.1% of surveyed households have heads with tertiary education and the lack of variation in data limits the results.

Third, households that are headed by males are less vulnerable, with a reduction in vulnerability of 25.7% (significant at the 10% level). A male-headed household also faces less aggregate risk. Hence, our result partially echoes Ligon and Schechter (2003)'s finding that male-headed Bulgarian households face lower aggregate risk. Unlike their related result that finds negligible effects on vulnerability, however, we find that households with male heads face significantly lower total vulnerability.

The marital status of the household head, however, has no affect on vulnerability. Nonetheless, households with heads who are married have 1.91% higher aggregate risk (significant at the 5% level) and have 12.1% lower unexplained risk (significant at the 5% level). Although it is difficult to interpret the latter result given the unknown nature of the unexplained risk, marriage of the household head may proxy for larger families, and such households may be more resilient to risks as a whole.

Households who own farm businesses face 49.2% more vulnerability than non-farm households (significant at the 1% level), with 57.8% increase in risk from poverty and a 1.112% reduction in aggregate risk (significant at the 1% and 10% levels, respectively). Since farm households face a substantially higher degree of vulnerability than non-farm households, non-farm income seems to be an important form of insurance against vulnerability in total consumption.

Households that have experienced some form of exogenous shocks have 28.3% lower vulnerability (significant at the 5% level). These households also face less poverty (significant at the 5% level), suggesting that such shocks reflect the deaths of relatively unproductive household members. That is, while the death of a household member who provides a main source of income will increase the household's vulnerability, the death of an unproductive member of a household may reduce the household's vulnerability because he or she ceases to claim a share of household resources (Van Cott 2000; Miguel 2005).

Table 4.4 shows that secondary education mitigates the effect of smoke exposure on vulnerability in total consumption. In particular, smoke raises the vulnerability of households whose heads have tertiary education while it lowers the vulnerability of households whose heads have secondary education (each significant at the 10% level). Smoke does not differentially influence the vulnerability of households whose heads have primary education.

4.6.2 Vulnerability in Food Consumption

Table 4.5 presents the correlates of each element of vulnerability in food consumption with the same set of household characteristics. Comparing the relationship between smoke and both measures of vulnerability implies that households who are unaffected by natural disasters are able to reduce their vulnerability in non-food consumption only. The effects of exposure to smoke on almost all elements of vulnerability in food consumption are statistically zero, except for the negligible reduction in idiosyncratic risk by 0.145% (significant at the 1% level) for a 1-unit increase in the TOMS Aerosol Index. This result implies that households who live in areas that are affected by smoke are no more vulnerable or likely to face poverty, aggregate risk, or idiosyncratic risk than others who live in areas unaffected by smoke.

Unlike total consumption, households with male heads have no statistically different level of vulnerability in food consumption. Neither do married household heads seem to be statistically different than single heads in terms of their effect on vulnerability in food consumption. However, the effect of education on vulnerability remains in food consumption: while households with heads who graduated from primary schools are no more or less vulnerable than households with heads who graduated from universities; households with heads who graduated from secondary schools face 33.8% less vulnerability and 0.157% less aggregate risk (significant at the 10% levels) than those with heads who graduated from universities.

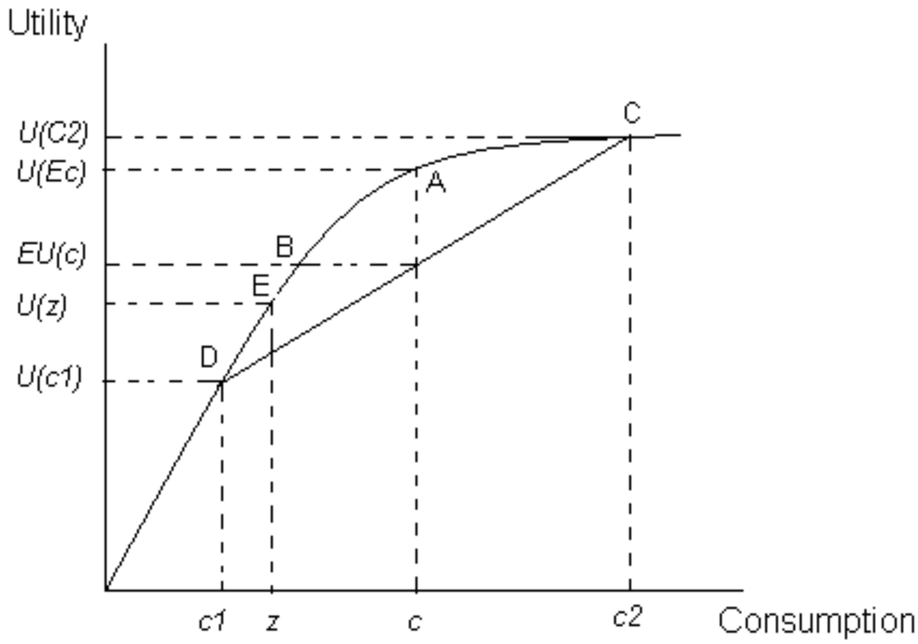
In addition to total consumption, farm households face a 32.4% increase in vulnerability in food consumption relative to non-farm households (significant at the 1% level). Of this increase, 26.1% comes from poverty risk, 1.47% comes from aggregate risk, and 6.37% comes from unexplained risk, with a negligible 0.16% reduction in idiosyncratic risk (all significant at the 5% level or higher). This result suggests that farm households are likely to have large investments in agricultural activities and are thus more vulnerable in food consumption to risks that affect crop output, including smoke from the 1997 forest fires. Unlike the analysis on total consumption, Table 4.6 shows that education does not influence the effect of smoke on vulnerability.

4.7 Discussion

This study contributes to our understanding of vulnerability by focusing on the role that the 1997 forest fires in Indonesia played in households' total consumption and food consumption. Using the decomposition method pioneered by Ligon and Schechter (2003), we find that households who live in areas unaffected by smoke from the 1997 forest fires were less vulnerable in total consumption, but they were no less vulnerable or likely to face poverty, aggregate risk, or idiosyncratic risk in food consumption than those who live in areas that were affected by smoke.

The results of this study have important policy implications. First, in contrast to a number of studies showing that female-headed households are not more or less vulnerable than male-headed households (e.g., Ligon and Schechter 2002), this chapter finds that the presence of a male household head reduces the household's vulnerability in total consumption. Second, we find that non-farm households are less vulnerable in both total and food consumption, suggesting that income diversification is an important factor in consumption smoothing. Third, the study provides ample evidence to support the value of education: not only do households with more educated household heads face less vulnerability in both total and food consumption, but those with heads who graduated from secondary schools have lower vulnerability in both total consumption food consumption, producing the largest percentage reductions in the vulnerability measures. Thus, promoting education seems to be an effective policy to empower female-headed households with tools to cope with risks. Given that only 25.1% of household heads in 1997 graduated from secondary school, policies to increase higher secondary school enrollment rates would help to reduce vulnerability.

Figure 4.1: Risk Aversion



Notes:
Refer to equation (1). The difference between the household's utility of expected consumption and the expected utility of consumption is measured by the distance between A and B, which reflects the household's risk. If we consider z to be analogous to a poverty line, then the difference between the household's utility of expected consumption and the utility of consumption bundle z that is measured by the distance between B and E reflects poverty.

Table 4.1: Summary Statistics

			Mean	Standard Deviation		
Variables	Description	Unit	1993	1997	1993	1997
Totalcons	Total consumption expenditures#	Rupiah	1.31	0.161***	6.053	0.243
Fcons	Food consumption expenditures#	Rupiah	0.208	0.158***	1.125	0.243
Age	Age of the head of household	Years	48.765	47.358***	16.002	14.256
Male	Household head is male	Dummy	0.769	0.818***	0.425	0.379
Married	Head of household is married	Dummy	0.748	0.724***	0.437	0.423
PrimaryEd	Head of households who graduated from primary school	Dummy	0.749	0.711***	0.434	0.452
SecondaryEd	Head of households who graduated from secondary school	Dummy	0.21	0.251	0.407	0.435
TertiaryEd	Head of households who graduated from college or university	Dummy	0.041	0.038	0.187	0.156
Farmbusp	Household's income from farm labor#	Rupiah	0.5	0.874***	1.253	1.263
Nfarmbusp	Household's income from non-farm labor#	Rupiah	1.361	1.819***	4.367	2.117
FarmHH	Households with a farm business	Dummy	0.249	0.256***	0.298	0.436
Debt	Household's amount of current debt#	Rupiah	0.476	1.548***	4.544	6.742
Shock	Household has experienced exogenous shocks in the last 5 years	Dummy	0.305	0.101***	0.47	0.306
Smoke	TOMS Aerosol Index	Number	-	0.505	-	0.759

Note: t-tests are conducted to show whether means are statistically different between 1993 and 1997.
Differences in the means are statistically significant at *** p<0.01, ** p<0.05, * p<0.1. #All values are in 100,000 Rupiahs.

Table 4.2: Estimation and Breakdown of Vulnerability in Total and Food Consumption

VARIABLES	Vulnerability	Poverty	Aggregate Risk	Idiosyncratic Risk	Unexplained Risk
Total Consumption	3.7905***	2.5112***	0.3479***	0.0040*	0.9177***
	[2.99, 4.45]	[1.85, 3.09]	[0.253, 0.446]	[-0.00021, 0.0352]	[0.762, 1.06]
Food Consumption	1.0365***	0.5059***	0.0125**	0.005138***	0.5125***
	[0.809, 1.28]	[0.362, 0.664]	[0.00062, 0.0398]	[0.00267, 0.0367]	[0.399, 0.617]

Note: Bootstrapped 95% confidence intervals are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Following the procedure established by Ligon and Schechter (2003), estimates are each decomposed into poverty, aggregate risk, idiosyncratic risk, and unexplained risk. Thus, the estimate of vulnerability in total consumption is the sum of the estimates of the four decomposed measures, and similarly for the estimate of vulnerability in food consumption. To calculate the contributions of each type of risk to vulnerability, compare the magnitudes of their percentage shares of the vulnerability estimate.
For example, poverty represents 2.51/3.79*100 = 66.25% of vulnerability in total consumption while aggregate risk is only 0.35/3.79*100 = 9.18% of vulnerability in total consumption.

Table 4.3: Vulnerability in Total Consumption and Household Characteristics

VARIABLES	Vulnerability (I)	Poverty (II)	Aggregate Risk (III)	Idiosyncratic Risk (IV)	Unexplained Risk (V)
Age	0.00341	0.00309	0.0000770	0.0000162	0.00000428
	(0.00358)	(0.00400)	(0.000205)	(0.0000539)	(0.00103)
Male	-0.257*	-0.213	-0.0150*	0.00333***	-0.0273
	(0.143)	(0.161)	(0.00822)	(0.00106)	(0.0494)
Married	0.0819	0.187	0.0191**	0.000422	-0.121**
	(0.160)	(0.176)	(0.00929)	(0.00114)	(0.0536)
PrimaryEd	-0.114	-0.121	0.0112	-0.00103	0.00566
	(0.135)	(0.149)	(0.00760)	(0.00240)	(0.0404)
SecondaryEd	-0.515**	-0.562**	0.0135	-0.00104	0.0440
	(0.230)	(0.222)	(0.0118)	(0.00184)	(0.0661)
FarmHH	0.492***	0.578***	-0.0112*	-0.00137	-0.0660**
	(0.112)	(0.126)	(0.00641)	(0.00102)	(0.0313)
Shock	-0.283**	-0.291**	0.00415	-0.00191*	0.0117
	(0.119)	(0.128)	(0.00658)	(0.00103)	(0.0307)
Smoke	0.0360*	0.0737***	0.00295	-0.00175***	0.0237
	(0.0182)	(0.0325)	(0.00383)	(0.000556)	(0.0183)
Observations	1143	1143	1143	1140	1140

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4: Vulnerability in Total Consumption and Household Characteristics (with interactions)

VARIABLES	Vulnerability (VI)	Poverty (VII)	Aggregate Risk (VIII)	Idiosyncratic Risk (IX)	Unexplained Risk (X)
Age	0.00303	0.00247	-0.0000339	-0.0000125	0.000572
	(0.00428)	(0.00480)	(0.000246)	(0.0000661)	(0.00124)
Male	-0.327**	-0.283	-0.0155	0.00366***	-0.0323
	(0.163)	(0.186)	(0.00962)	(0.00126)	(0.0589)
Married	0.0690	0.210	0.0202*	0.000633	-0.160**
	(0.185)	(0.205)	(0.0109)	(0.00137)	(0.0636)
PrimaryEd	0.00730	0.00140	0.00540	-0.000765	0.00116
	(0.163)	(0.182)	(0.00933)	(0.00316)	(0.0506)
SecondaryEd	-0.261	-0.354	0.0211*	-0.00377***	0.0767
	(0.267)	(0.262)	(0.0127)	(0.00140)	(0.0847)
FarmHH	0.453***	0.584***	-0.0134*	-0.00166	-0.115***
	(0.135)	(0.154)	(0.00798)	(0.00132)	(0.0395)
Shock	-0.253*	-0.249	0.00193	-0.00213*	-0.00533
	(0.146)	(0.156)	(0.00805)	(0.00129)	(0.0379)
Smoke	0.0258*	0.0173*	-0.0190	-0.00106	-0.0826
	(0.0134)	(0.008)	(0.0155)	(0.00227)	(0.0736)
PrimaryEd X Smoke	-0.286*	-0.285*	0.0114	-0.000489	0.0133
	(0.162)	(0.173)	(0.00865)	(0.00191)	(0.0412)
SecondaryEd X Smoke	-0.588*	-0.472	-0.0166	0.00560	-0.0872
	(0.317)	(0.291)	(0.0199)	(0.00357)	(0.0691)
Observations	1143	1143	1143	1140	1140

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.5: Vulnerability in Food Consumption and Household Characteristics

VARIABLES	Vulnerability (I)	Povert (II)	Aggregate Risk (III)	Idiosyncratic Risk (IV)	Unexplained Risk (V)
Age	0.000156	-0.000154	0.00000881	0.0000245	0.000256
	(0.00273)	(0.00233)	(0.0000134)	(0.0000341)	(0.000776)
Male	-0.122	-0.118	-0.000730	0.00139*	-0.00409
	(0.124)	(0.107)	(0.000551)	(0.000714)	(0.0311)
Married	-0.0963	-0.0885	0.000141	0.000267	-0.00776
	(0.140)	(0.119)	(0.000630)	(0.000806)	(0.0336)
PrimaryEd	-0.111	-0.107	-0.000528	-0.000821	-0.00179
	(0.101)	(0.0840)	(0.000500)	(0.00177)	(0.0357)
SecondaryEd	-0.338*	-0.231	-0.00157*	-0.000217	-0.105**
	(0.183)	(0.147)	(0.000900)	(0.00148)	(0.0426)
FarmHH	0.324***	0.261***	0.00147***	-0.00161**	0.0637**
	(0.0896)	(0.0762)	(0.000404)	(0.000725)	(0.0282)
Shock	-0.112	-0.105	-0.000688	-0.000002	-0.00558
	(0.0945)	(0.0790)	(0.000447)	(0.00105)	(0.0286)
Smoke	0.0284	0.0201	0.0000376	-0.00145***	0.00928
	(0.0558)	(0.0478)	(0.000261)	(0.000413)	(0.0159)
Observations	567	567	567	566	566

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6: Vulnerability in Food Consumption and Household Characteristics (with interactions)

VARIABLES	Vulnerability (VI)	Poverty (VII)	Aggregate Risk (VIII)	Idiosyncratic Risk (IX)	Unexplained Risk (X)
Age	0.00152	-0.00143	-0.00000185	0.0000239	-0.000116
	(0.00346)	(0.00291)	(0.0000167)	(0.0000464)	(0.000894)
Male	-0.0806	-0.0949	-0.000588	0.00182**	0.0131
	(0.15)	(0.129)	(0.000656)	(0.000894)	(0.0370)
Married	-0.145	-0.137	-0.0000354	-0.0000602	-0.00752
	(0.172)	(0.146)	(0.000762)	(0.00106)	(0.0408)
PrimaryEd	-0.0218	-0.0182	-0.0002	-0.000461	-0.00287
	(0.132)	(0.108)	(0.000627)	(0.00266)	(0.0444)
SecondaryEd	-0.161	-0.0953	-0.000764	-0.00158	-0.0637
	(0.233)	(0.189)	(0.00103)	(0.00145)	(0.0541)
FarmHH	0.384***	0.306***	0.00172***	-0.00207**	0.0785**
	(0.115)	(0.0966)	(0.000492)	(0.00100)	(0.0364)
Shock	-0.108	-0.089	-0.000696	0.000566	-0.0188
	(0.123)	(0.100)	(0.000566)	(0.00148)	(0.0364)
Smoke	-0.0938	-0.0865	-0.000877	-0.00103	-0.00565
	(0.225)	(0.197)	(0.00119)	(0.00146)	(0.0593)
PrimaryEd X Smoke	-0.16	-0.154	-0.000617	-0.000605	-0.00399
	(0.118)	(0.101)	(0.000621)	(0.00154)	(0.0417)
SecondaryEd X Smoke	-0.307	-0.246	-0.00143	0.00228	-0.0623
	(0.219)	(0.181)	(0.00129)	(0.00213)	(0.0485)
Observations	567	567	567	566	566

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.8 Appendix G

The second bracketed term in equation (4.3) that measures idiosyncratic risk can be rewritten as:

$$
\begin{aligned}
&EU^i(E(c_t^i|\bar{x}_t)) - EU^i(Ec_t^i|\bar{x}_t, x_t^i)) \\
&\qquad = [EU^i i(E(c_t^i|\bar{x}_t)) - EU^i(E(c_t^i|\bar{x}_t, x_{1t}^i))] \\
&\qquad + [EU^i i(E(c_t^i|\bar{x}_t, x_{1t}^i)) - EU^i(E(c_t^i|\bar{x}_t, x_{1t}^i, x_{2t}^i))] \\
&\qquad ... \\
&\qquad + [EU^i(E(c_t^i|\bar{x}_t, x_{1t}^i, ..., x_{(k-1)t}^i)) - EU^i(E(c_t^i|\bar{x}_t, x_{1t}^i, ..., x_{kt}^i))]
\end{aligned}
\tag{4.5}
$$

Suppose that x_{1t}^i represents the part of household's farm labor income that is orthogonal to household and time effects; that x_{2t}^i represents the part of current household debt that is orthogonal to household effects, time effects, and household's farm labor income; and that x_{3t}^i represents the part of the household's off-farm income that is orthogonal to all the other variables. Then, the first bracketed term gives a measure of the welfare loss that can be predicted using variation in household i's farm labor income, the second term measures the change in the prediction of welfare loss after including data on current household debt, and the third term measures the change after including data on household's off-farm labor.

Bibliography

[1] Aguilar, Arturo, and Marta Vicarelli (2011). "El Nino and Mexican Children: Medium-Term Effects of Early-Life Weather Shocks on Cognitive and Health Outcomes," *mimeo.*

[2] Akerlof, George A. (1970). "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 84 (3): 488-500.

[3] Amin, Sajeda, Ashok S. Rai, and Giorgio Topa (2003). "Does Microcredit Reach the Poor and Vulnerable? Evidence from Northern Bangladesh," *Journal of Development Economics*, 70 (1): 59-82.

[4] Annan, Kofi (1999). "An Increasing Vulnerability to Natural Disasters," International Herald Tribune. Retrieved November 28, 2919 from http://www.un.org/News/ossg/sg/stories/articleFull.asp?TID=34&Type=Article.

[5] Bane, Mary J., and David T. Ellwood (1986). "Slipping Into and Out of Poverty: The Dynamics of Spells," *The Journal of Human Resources*, 21 (1): 1-23.

[6] Banerjee, Abhijit, and Esther Duflo (2005). "Growth Theory through the Lens of Development Economics," in *Handbook of Economic Growth*, Philippe Aghion and Steven Durlauf, eds. (Amsterdam: Elsevier Press, 2005).

[7] Banerjee, Abhijit, and Kaivan Munshi (2004). "How Efficiently is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur," *Review of Economic Studies*, 71: 19-42.

[8] Banerjee, Lopamudra (2007). "Effect of Flood on Agricultural Wages in Bangladesh: An Empirical Analysis," *World Development*, 35(11): 1989-2009.

[9] Banerjee, Abhijit V., and Andrew F. Newman (2007). "Occupational Choice and the Process of Development," *Journal of Political Economy*, 101(21): 274-298.

[10] Bardhan, Pranab K. (1979). "Labor Supply Functions in a Poor Agrarian Econ-

omy," *The American Economic Review*, 69(1): 73-83.

[11] Barrett, Christopher B. (1999). "On Vulnerability, Asset Poverty and Subsidiarity," Comments to the Ford/Rockefeller Foundations Seminar Series *Managing Vulnerability and Shocks within the Agro-Food System*. New York, May 26, 1999.

[12] Beard, Victoria A. (2007). "Household Contributions to Community Development in Indonesia," *World Development*, 35(4): 607-25.

[13] Becchetii, Leonardo, and Stefano Castriota (2011). "Does Microfinance Work as a Recovery Tool After Disasters? Evidence from the 2004 Tsunami," *World Development*, 39(6): 898-912.

[14] Beegle, Kathleen, Rajeev H. Dehejia, and Roberta Gatti (2006). "Child Labor and Agricultural Shocks," *Journal of Development Economics*, 81(1): 80-96.

[15] Begazo-Gomez, Tania, Alan Fuchs, and Ari Perdana (2006). "Better-or not? Community Participation, Consumption Smoothing and Household Head Employment in Indonesia," *CSIS Working Paper Series*, WPE 096.

[16] Bigsten, Arne, Anders Isaksson, Mans Soderbom, Paul Collier, Albert Zeufack, Stefan Dercon, Marcel Fafchamps, Jan Willem Gunning, Francis Teal, Simon Appleton, Bernard Gauthier, Abena Oduro, Remco Oostendorp, and Cathy Pattillo (2000). "Rates of Return on Physical and Human Capital in Africa's Manufacturing Sector,' *Economic Development and Cultural Change*, 48(4): 801-27.

[17] Blundell, Richard, Pierre-Andre Chiappori, and Costas Meghir (2005). "Collective Labor Supply with Children," *Journal of Political Economy*, 113(6): 1277-1306.

[18] Blundell, Richard, Pierre-Andre Chiappori, Thierry Magnac, and Costas Meghir (2005). "Collective Labor Supply: Heterogeneity and Non-Participation," *Review of Economic Studies*, 74: 417-45.

[19] Browning, Martin, and Mette Gortz (2005). "Spending Time and Money within the Household," *The Scandinavian Journal of Economics*, 114(3): 681-704.

[20] Carney, Diana, Michael Drinkwater, Tamara Rusinow, Koos Neefjes, Samir Wanmali, and Naresh Singh (1999). *Livelihood Approaches Compared: A Brief Comparison of the Livelihoods Approaches of DFID, CARE, Oxfam, and UNDP*. (London: DFID, 1999).

[21] Carter, Michael R., and Julian May (1999). "Poverty, Livelihood and Class in Rural South Africa," *World Development*, 27 (1): 1-20.

[22] Center for Research on the Epidemiology of Disasters (CRED) (2009). Annual

Disaster Statistical Review: The Numbers and Trends 2008. Brussels (Belgium), May.

[23] Chen, Shaohua, Ren Mu and Martin Ravallion (2009). "Are There Lasting Impacts of Aid to Poor Areas," *Journal of Public Economics*, 93: 512-28.

[24] Chiappori, Pierre-Andre (1988). "Rational Household Labor Supply," *Econometrica*, 56(1): 63-90.

[25] Chiappori, Pierre-Andre, Bernard Fortin, and Guy Lacroix (2002). "Marriage Market, Divorce Legislation, and Household Labor Supply," *Journal of Political Economy*, 110(1): 37-72.

[26] Currie, Janet, and Firouz Gahvari (2008). "Transfers in Cash and In-Kind: Theory Meets the Data," *Journal of Economic Literature*, 46(2): 333-83.

[27] Czura, Kristina, and Stefan Klonner (2012). "Evidence from Roscas and the Indian Ocean Tsunami," *mimeo.*

[28] de Mel, Suresh, David McKenzie, and Christopher Woodruff (2008). "Returns to Capital in Microenterprises: Evidence from a Field Experiment," *Quarterly Journal of Economics*, 123 (4): 1329-72.

[29] de Mel, Suresh, David McKenzie, and Christopher Woodruff (2012). "One-Time Transfers of Cash or Capital Have Long-Lasting Effects of Microenterprises in Sri Lanka," *Science*, 335 (962): 962-66.

[30] Deaton, Angust (1997). *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy.* (Washington, D.C.: World Bank Publications, 1999).

[31] Dodlova, Marina, Kristin Gobel, Michael Grimm, and Jann Lay (2015). "Constrained Firms, Not Subsistence Activities: Evidence on Capital Returns and Accumulation in Peruvian Microenterprises," *Labour Economics*, *forthcoming.*

[32] Donni, Olivier (2008). "Labor Supply, Home Production, and Welfare Comparisons," *Journal of Public Economics*, 92: 1720-737.

[33] Eilerts, Gary S. (1994). "An Assessment of Vulnerability in Zimbabwe's Communal Lands," USAID Famine Early Warning System (FEWS), Project 698-0466.

[34] Emergency Events Database (2011). Retrieved on the World Wide Web on 4 March 2011: http://www.emdat.be/Database/DisasterList/ emdat_display_list.php.

[35] Emergency Events Database (2013). Retrieved on the World Wide Web on 20

December 2013: *http://www.emdat.be/disaster-list*.

[36] Fafchamps, Marcel, Christopher Udry, and Katherine Czukas (1998). "Drought and Saving in West Africa: Are Livestock a Buffer Stock," *Journal of Development Economics*, 55: 273-305.

[37] Fafchamps, Marcel, David McKenzie, Simon Quinn and Christopher Woodruff (2014). "Microenterprise growth and the flypaper effect: Evidence from a Randomized Experiment in Ghana," *Journal of Development Economics*, 106: 211-26.

[38] FAO/WFP (2005). *Food Supply and Demand Assessment for Aceh Province.* Special Report prepared by Gunjal, Kisan , Cheng Fang, Siemon Hollema, and Issa Sanog. Rome, December.

[39] Frankenberg, Elizabeth, Lynn A. Karoly, Paul Gertler, Sulistinah Achmad, I.G.N. Agung, Sri Harijati Hatmadji, and Paramita Sudharto (1995). The 1993 Indonesian Family Life Survey (IFLS): Overview and Field Report. RAND, Santa Monica, CA.

[40] Frankenberg, Elizabeth, Duncan Thomas, and Kathleen Beegle (1999). "The Real Costs of Indonesian Economic Crisis: Preliminary Findings from the Indonesian Family Life Surveys," Labor and Population Program Working Paper Series, 99-04.

[41] Frankenberg, Elizabeth, Douglas McKee, and Duncan Thomas (2005). "Health Consequences of Forest Fires in Indonesia," *Demography*, 42 (1): 109-29.

[42] Fomby, Thomas, Yuki Ikeda, and Norman V. Loayza (2011). "The growth aftermath of natural disasters," *Journal of Applied Econometrics*, 28(3): 412-34.

[43] Freire, Tiago, Vernon J. Henderson, and Ari, Kuncoro (2011). "Volunteerism After the Tsunami: Democratization and Aid," *mimeo*.

[44] Friedman, Milton, and L. J. Savage (1948). "The Utility Analysis of Choices Involving Risk," *The Journal of Political Economy*, 56 (4): 279-304.

[45] Fuller, Douglas O., and M. Fulk (2000). "Comparison of NOAA-AVHRR and DMSP-OLS for Operational Fire Monitoring in Kalimantan, Indonesia," *International Journal of Remote Sensing*, 21 (1): 181-87.

[46] Gagnon, Jason (2013). "Natural Disaster, Emigration and Household Labor Behavior in Honduras," *mimeo*.

[47] Goldberg, Jessica (2014). "Kwacha Gonna Do? Experimental Evidence about Labor Supply In Rural Malawi," *mimeo*.

[48] Guarcello, Lorenzo, Fabrizia Mealli, and Furio Camillo Rosati (2010). "Household Vulnerability and Child Labor: The Effect of Shocks, Credit Rationing, and Insurance," *Journal of Population Economics*, 23: 169-98.

[49] Halliday, Timothy (2006). "Migration, Risk, and Liquidity Constraints in El Salvador," *Economic Development and Cultural Change*, 54(4): 893-925.

[50] Heckman, James J. (1993). "What Has Been Learned about Labor Supply in the Past Twenty Years?" *The American Economic Review*, 83(2): 116-21.

[51] Hellwig, Tineke, and Eric Tagliacozzo (2009). The Indonesia Reader: History, Culture, Politics. (Duke University Press Books, 2009).

[52] Hochrainer, Stefan (2009). "Assessing the Macroeconomic Impacts of Natural Disasters. Are there any," World Bank Policy Research Working Paper, No. 4968.

[53] Hornbeck, Richard (2012). "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe," *American Economic Review*, 102 (4): 1477-507.

[54] Jacoby, Hanan G. (1997). "Self-Selection and the Redistributive Impact of In-Kind Transfers: An Econometric Analysis," *The Journal of Human Resources*, 32(2): 233-49.

[55] Janes, Laurin (2013). "Can Capital Grants Help Microenterprises Reach the Productivity Level of SMEs? Evidence from an Experiment in Sri Lanka," CSAE Working Paper, WPS/2013-18.

[56] Janssen, Hilde (2005). "Study on the Post-tsunami Rehabilitation of Fishing Communities and Fisheries-based Livelihoods in Indonesia," International Collective in Support of Fishworkers, Banda Aceh/Jakarta, December.

[57] Krishnan, Karthik, Debarshi Nandy, and Manju Puri (2014). "Does Financing Spur Small Business Productivity: Evidence from a Natural Experiment," *Review of Financial Studies*, *forthcoming*.

[58] Garces, L. A. Tewfik, M. Pido, N. Fatan, D. Adhuri, N. Andrew, and M. Dey (2006). "Fisheries Rehabilitation in Post-Tsunami Aceh: Status and Needs from Participatory Appraisals," NAGA, WorldFish Center Quarterly, 29(3 & 4): 19-30.

[59] Glewwe, Paul, and Gillette Hall (1998). "Are Some Groups More Vulnerable to Macroeconomic Shocks than Others? Hypothesis Tests Based on Panel Data from Peru," *Journal of Development Economics*, 56: 181-206.

[60] Glover, David, and Timothy Jessup (1999). *Indonesia's Fires and Haze: The*

Cost of Catastrophe. (Singapore: Institute of Southeast Asian Studies, 1999).

[61] Henderson, J. Vernon, and Yong Suk Lee (2014). "Organization of Disaster Aid Delivery: Spending Your Donations," *Economic Development and Cultural Change, forthcoming.*

[62] Jacoby, Hanan, and Emmanuel Skoufias (1997). "Risk, Financial Markets, and Human Capital in a Developing Country," *Review of Economic Studies*, 64(3): 311-35.

[63] Jalan, Jyotsna, and Martin Ravallion (1998). "Transient Poverty in Post Reform China," *Journal of Comparative Economics*, 26: 338-57.

[64] Jayachandran, Seema (2006). "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, 114(3): 538-75.

[65] Jayachandran, Seema (2009). "Air Quality and Early-Life Mortality: Evidence from Indonesia's Wildfires," *Journal of Human Resources*, 44 (4): 916-54.

[66] Keogh, Eamonn (1997). "Geographical Targeting of Districts in Zimbabwe," (Harare: Social Development Fund, Government of Zimbabwe).

[67] Ketterings, Quirine M., Titus Tri Wibowo, Meine van Noordwijk, and Eric Penot (1999). "Farmers' Perspectives on Slash-and-Burn as a Land Clearing Method for Small Scale Rubber Producers in Sepunggur, Jambi Province, Sumatra, Indonesia," *Forest Ecology and Management*, 120 (1-3): 157-69.

[68] Khandker, Shahldur (2007). "Coping with flood: role of institutions in Bangladesh," *Agricultural Economics*, 36(2): 169-80.

[69] Kiviet, Jan F. (1995). "On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models," *Journal of Econometrics*, 68(1): 53-78.

[70] Kochar, Anjini (1999). "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India," *Review of Economics and Statistics*, 81(1): 50-61.

[71] Kreimer, Alcira, and Margaret Arnold (2000). *Managing Disaster Risk in Emerging Economies*, (Washington D.C.: World Bank Publications, 2000).

[72] Ligon, Ethan, and Laura Schechter (2002). "Measuring Vulnerability: The Director's Cut," UN/WIDER Discussion Paper, 2002/86.

[73] Ligon, Ethan, and Laura Schechter (2003). "Measuring Vulnerability," *Economic Journal*, 113 (March): C95-C102.

[74] Ligon, Ethan, and Laura Schechter (2004). "Evaluating Different Approaches to Estimating Vulnerability," Social Protection Discussion Paper Series, No.0410.

[75] Loayza, Norman V., Eduardo Olaberria, Jamele Rigolini, and Luc Christiaensen (2012). "Natural Disasters and Growth. Going beyond the Averages," *World Development*, 40(7): 1317-336.

[76] Lymer, David, Simon Funge-Smith, and Dominique Greboval (2009). "The Fishing Fleet in Aceh Province, Indonesia," FAO Regional Office for Asia and the Pacific, Bangkok, Thailand. RAP Publication. 39 pp.

[77] Maccini, Sharon, and Dean Yang (2009). "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall.," *American Economic Review*, 99(3): 1006-026.

[78] Maxwell, Daniel, Carol Levin, Margaret Armar-Klemesu, Marie Ruel, Saul Morries, and Clement Ahiadeke (2000). "Urban Livelihoods and Food and Nutrition Security in Greater Accra, Ghana," Research Report 112. (Washington D.C.: International Food Policy Research Institute, 2000).

[79] McKenzie, David, and Christopher Woodruff (2006). "Do Entry Costs Provide an Empirical Basis for Poverty Traps? Evidence from Mexican Microenterprises," *Economic Development and Cultural Change*, 55: 3-42.

[80] McKenzie, David, and Christopher Woodruff (2008). "Experimental Evidence on Returns to Capital and Access to Finance in Mexico," *World Bank Economic Review*, 22(3): 457-82.

[81] Miguel, Edward (2005). "Poverty and Witch Killing," *Review of Economic Studies*, 72: 1153-172.

[82] Miguel, Edward, Paul Gertler, and David I. Levine (2006). "Does Industrialization Build or Destroy Social Networks?" *Economic Development and Cultural Change*, 54(2): 287-317.

[83] Nose, Manabu (2013). "Enduring Impacts of Aid Quality on Job Choices. The Case of the 2004 Tsunami in Aceh," World Bank Policy Research Working Paper, No. 6514.

[84] Nose, Manabu (2014). "Micro Responses to Disaster Relief Aid: Design Problems for Aid Efficacy," *The Quarterly Journal of Economics*, 84 (3): 488-500.

[85] Noy, Ilan (2009). "The Macroeconomic Consequences of Natural Disasters," *Journal of Development Economics*, 88: 221-31.

[86] Oettinger, Gerald S. (1999). "An Empirical Analysis of the Daily Labor Supply of Stadium Vendors?" *Journal of Political Economy*, 107(2): 360-92.

[87] Paxson, Christina H. (1992). "Using Weather Variability To Estimate the Response of Savings to Transitory Income in Thailand," *American Economic Review*, 82(1): 13-33.

[88] Pradhan, Menno, Asep Suryahadi, Sudarno Sumarto, and Lant Pritchett (2000). "Measurements of Poverty in Indonesia: 1996, 1999, and Beyond," Policy Research Working Paper, No.2438.

[89] Pritchett, Lant, Asep Suryahadi, and Sudarno Sumarto (2000). "Quantifying Vulnerability to Poverty: A Proposed Measure, Applied to Indonesia," Policy Research Working Paper, No.2437.

[90] Raddatz, Claudio (2009). "The Wrath of God. Macroeconomic Costs of Natural Disasters," World Bank Policy Research Working Paper, No. 5039.

[91] Ravallion, Martin, and Benu Bidani (1994). "How Robust is a Poverty Profile," *The World Bank Economic Review*, 8 (1): 75-102.

[92] Rose, Elaina (2001). "Ex Ante and Ex Post Labor Supply Response to Risk in a Low-Income Area," *Journal of Development Economics*, 64: 371-88.

[93] Rosenzweig, Mark R. (1978). "Rural Wages, Labor Supply, and Land Reform: A Theoretical and Empirical Analysis," *The American Economic Review*, 68 (5): 847-861.

[94] Rosenzweig, Mark R., and Christopher Udry (2014). "Rainfall Forecasts, Weather and Wages over the Agricultural Production Cycle," NBER Working Paper, No. 19808.

[95] Salvanes, Kjell G., and Frode Steen (1994). "Testing for Relative Performance between Seasons in a Fishery," *Land Economics*, 70 (4): 431-47.

[96] Selcuk, Faruk, and Erinc Yeldan (1992). "On the Macroeconomic Impact of the August 1999 Earthquake in Turkey: A First Assessment," *Applied Economics Letters*, 8(7): 483-88.

[97] Siba, Eyerusalem (2015). "Returns to Physical Capital in Ethiopia: Comparative Analysis of Formal and Informal Firms," *World Development*, 68: 215-29.

[98] Strobl, Eric (2012). "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions," *Journal of Development Economics*, 97(1): 130-41.

[99] Thorburn, Craig (2009). "Livelihood Recovery in the Wake of the Tsunami in Aceh," *Bulletin of Indonesian Economic Studies*, 45 (1): 85-105.

[100] Total Ozone Mapping Spectrometer (TOMS) (2011). Re-

trieved on the World Wide Web on 4 January 2011: http://toms.gsfc.nasa.gov/aerosols/aerosols_v8.html.

[101] Trohanis, Zoe Elena, Zuzana Svetlosakova, and Helene Carlsson-Rex (2011). "Making Women's Voices Count in Natural Disaster Programs in East Asia and the Pacific," East Asia and Pacific Region Social Development Notes, World Bank, Washington, D.C.

[102] Udry, Christopher (1994). "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria," *The Review of Economic Studies*, 61(3): 495-526.

[103] Udry, Christopher, and Santosh Anagol (2006). "The Return to Capital in Ghana," *American Economic Review*, 96(2): 388-93.

[104] United Nations Development Program (1998). "Kebakaran Hutan dan Lahan di Indonesia: Dampak, Faktor, dan Evaluasi," [Forest and Land Fires in Indonesia: Consequences, Factors, and Evaluation] (Jakarta: Kantor Menteri Negara Linkungan Hidup, 1998).

[105] Vella, Venanzio, and Maurizio Vichi (1997). "Classification of Poverty in South Africa Using Cluster Analysis," *mimeo.*

[106] Van Cott, Donna L. (2000). "A Political Analysis of Legal Pluralism in Bolivia and Colombia," *Journal of Latin American Studies*, 32 (1): 207-34.

[107] Webb, Patrick (1993). "Coping with Drought and Food Insecurity in Ethiopia," *Disasters*, 17 (1): 33-47.

[108] Wisner, Ben, Piers Blaikie, Terry Cannon, and Ian Davis (1994). *At Risk: Natural Hazards, PeopleÕs Vulnerability, and Disaster.* (New York: Routledge, 1994).

[109] Wooldridge, Jeffrey (2007). "Inverse probability weighted estimation for general missing data problems," *Journal of Econometrics*, 141(2): 1281-301.

[110] World Bank (2000). *World Development Report 2000/2001: Attacking Poverty,* (Washington D.C.: World Bank Publications, 2000).

[111] World Bank (2011). Natural Hazards, UnNatural Disasters, The Economics of Effective Prevention, (World Bank Publications, 2010).

[112] Zylberberg, Yanos (2010). "Do Tropical Typhoons Smash Community Ties? Theory and Evidence from Vietnam," *mimeo.*