Evolution of Wealth and Consumption in the Aftermath of a Major Natural Disaster

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Abstract

Natural disasters can have catastrophic personal and economic effects, particularly in low-resource settings. Major natural disasters are becoming more frequent, so rigorous understanding of their effects on long-term economic wellbeing is fundamentally important in order to mitigate their impacts on exposed populations. In this paper, I investigate the effects of the 2004 Indian Ocean tsunami on real consumption and assets at the individual level. I also examine the heterogeneity of those impacts, and the related effects on inequality. Taking individual-specific heterogeneity into account with fixed effects, I find individuals living in heavily damaged areas experience major declines in real consumption and assets, and do not recover in the long term. These results are strikingly different than results that do not consider price effects, as well as previously published macroeconomic results. I also find significant heterogeneity by age, education-level, pre-tsunami socioeconomic status, and whether an individual went into a refugee camp. The tsunami resulted in large, long-term declines in asset inequality, and a temporary increase in consumption inequality that returns to near pre-tsunami levels in the long run.

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1. Introduction

Natural disasters are increasing in both frequency and magnitude across the globe because of rising land and sea temperatures, greater encroachment of populations on fragile environments, and closer interactions among humans and other species. The initial impacts of these disasters can be devastating, particularly among the poorest who have the fewest resources to call on to buffer negative shocks and thereby have limited scope for consumption smoothing (Kochar, 1995; Henry, Spencer & Strobl, 2020). On one hand, there is evidence that individuals and families adopt behaviors to mitigate the negative impacts of these disasters. These behavioral responses have been shown to play an important role in low-resource settings where markets are incomplete and liquidity constraints bind (Frankenberg, Smith & Thomas, 2003; Stillman & Thomas, 2008). On the other hand, changes in the distribution of wealth at the time of a disaster can be magnified if those at the top of the distribution are better positioned to exploit new opportunities that arise because of the disaster (Ferreira & Ravallion, 2008). There is a paucity of scientific evidence on the immediate and longer-term impacts of large-scale disasters on the level and distribution of economic wellbeing of a population. This research is designed to contribute to this gap in the literature and, thereby, provide the evidence base necessary to design effective aid and reconstruction programs.

The objectives of this paper are threefold. The first is to empirically document the evolution of wealth and consumption over the short and longer-term after a major natural disaster, using uniquely rich longitudinal data collected before and after the 2004 Indian Ocean earthquake and tsunami. The second is to investigate the impact of the disaster on the distribution of these indicators of economic wellbeing over the short and long term. Third, this paper leverages the longitudinal nature of the data to investigate the impacts of behavioral responses, such as moving to refugee camps, in the immediate aftermath of the tsunami on subsequent economic outcomes.

I examine the 2004 Indian Ocean tsunami in Indonesia, which was completely unanticipated. Furthermore, the damage caused by the tsunami depended on idiosyncratic features of the land and seabed, so this research treats the variation in initial shock to economic wellbeing as plausibly exogenous (Frankenberg et al., 2012). This is not possible with many other natural disasters, in which exposure is endogenous to socioeconomic factors and associated behavioral responses to avoid exposure (Baker, 1991).

The consensus regarding the economic effects of natural disasters in the short term suggests that they generally have negative effects on wealth and income, despite insurance and humanitarian aid smoothing financial exposure to the shock (Guimaraes, Hefner, & Woodward, 1993; Schmacher & Strobl, 2011). In the short term, disruption to markets, and direct losses of property and livelihoods paint clear negative effects of disaster exposure, beyond the immense human costs disasters can exact. In the long term, individual and institutional responses to natural disasters – such as migration, reconstruction, and aid – make the long-term effects of natural disasters a priori ambiguous.

Little previous work documents the long-term effects of major natural disasters on wealth and income, though most of the macroeconomic evidence that does exist suggests neutral or negative effects of natural disasters over longer time horizons (Cavallo et al., 2013; Hsiang & Jina, 2014). In sharp contrast, a recent paper from 2019 that studies the same 2004 tsunami this paper investigates, suggests improved macroeconomic outcomes in provinces impacted by the tsunami, positing that structural economic shifts away from agriculture improved growth (Heger & Neumayer, 2019).

Much of the economic literature following natural disasters is focused on aggregate measures of wealth and income. This makes it difficult to understand the implications of exposure for individuals. Specifically, the incidence of natural disasters is typically not uniform across entire regions, and aggregate data masks differences amongst individual vulnerability to a given natural disaster. Some individuals are typically much more directly affected than others in a given region, and evaluation of macroeconomic outcomes may not show the true effects on people directly affected. Furthermore, aggregate evidence, while it can be informative, does not capture the evolution of well-being of individuals, and cannot address the heterogeneity in these pathways across subgroups of the population. In particular, recovery trajectories and ability to consumption smooth are likely dependent on a variety of factors – such as human capital or gender (Frankenberg et al., 2003).

Beyond this, previous literature on disasters suggests that market distortions in the short term, and structural economic changes in the long term due to natural disasters may shift price levels in affected areas. Previous literature that fails to take into account potential price effects on real economic wellbeing may be understating the costs of exposure.

Thus, the first contribution of this paper is that I utilize uniquely rich population-representative *individual-level* longitudinal data to rigorously identify causal *real* impacts of exposure to the tsunami in the long term. This data includes a pre-tsunami baseline that is population-representative and was designed to study the aftermath of the tsunami with detailed individual, household, and community data (including geographically detailed data on prices). Prices changed dramatically, particularly in the most damaged areas, and failure to take that into account results in substantively misleading conclusions. Furthermore, using this longitudinal data I am able to utilize an individual fixed effects approach, controlling for individual specific factors that may shape behavioral responses to the tsunami such as willingness to take risk, propensity to take on new challenges, or unobserved components of pre-tsunami human capital that are unobserved.

Using these individual fixed effects, I find that generally speaking, in terms of real per capita expenditure (PCE), everyone reduced their expenditure in real terms immediately after the tsunami, irrespective of where they were living. Among those in the most damaged areas at the time of the tsunami, this largely reflects much higher prices than in the areas that were not as badly damaged. Whereas pre-tsunami, those individuals who were living in areas that were subsequently the most damaged tended to have higher levels of real PCE, that advantage has disappeared within two years of the tsunami and, 10 years after the tsunami, people who lived in heavily damaged areas have lower real PCE than both people in other damage zones and their own baseline. In terms of assets, individuals living at the time of the tsunami in those areas that were most heavily damaged lost about half their assets in the disaster, and even 10 years later, they had not recovered. In moderately damaged areas, individuals lost a significant portion of their assets, but by 10 years later had recovered and had more assets than reported at baseline. With regard to assets, since they were measured retrospectively, individuals who lost significant assets are likely prone to overstate their losses, so the portion of assets lost in heavily damaged areas that may be inflated by reporting is uncertain. Between both measures, however, it is clear that individuals who were living in the most heavily affected areas at the time of the tsunami had substantial negative outcomes in both the short and long term.

These results provide a foundation for exploiting the individual-level longitudinal data to investigate heterogeneity in effects of exposure to a major natural disaster on different pre-disaster subgroups. Substantial evidence discusses and documents varying degrees of vulnerability to climate shocks amongst different parts of the population. This evidence underscores that individuals of lower socioeconomic status tend to be more vulnerable to natural disasters, and that the ability of individuals to consumption smooth is fundamental to natural disaster resilience. Previous literature suggests that access to consumption smoothing mechanisms - such as credit (formal or informal), ability to shift leisure over time to work, and savings/assets, to name a few – is largely determined by individual characteristics such as gender, human capital, age, and urban/rural status. Thus, I focus my analyses on these characteristics.

The results from this paper show substantial differences between the recovery trajectories of men and women. With regard to PCE, males and females see similar negative effects in the year after the tsunami, but males living in heavily damaged areas see faster growth in PCE than females in the long term, potentially reflecting differential abilities to earn income in the long term. Looking at real assets, in heavily damaged areas, males lose significantly more real assets than females after the tsunami, and do not recover them as quickly. This is consistent with previous evidence from Indonesia that suggests women's asset holdings tend to be different from men's, particularly that women hold a larger proportion of assets as gold (Wolf, 1991), which may have been less vulnerable to tsunami damage.

I also find that individuals who had higher socioeconomic status before the tsunami, either through higher education, higher levels of assets, or higher levels of PCE, do not recover as well in the long-term as individuals of lower socioeconomic status. While there is some evidence that higher education individuals are able to shield losses of assets and PCE in the short term, in the long term the evidence suggests that individuals with lower pre-tsunami socioeconomic status experienced substantial comparative improvements in economic wellbeing.

This paper also investigates any differences in the tsunami's impact on those who went to refugee camps in the aftermath. While the decision to go to a refugee camp cannot be considered exogenous, the individual fixed effect will control for the time-invariant component of propensity to move, willingness to take risk, and other important components of the decision to go to a refugee camp. I find that in the short term, going to a refugee camp partially protected real PCE, though in the long term this effect dissipates. I also find that with regard to assets, women from highly damaged areas who went to camps have similar assets to women who did not in the long run, despite losing more immediately after the tsunami. In contrast, men who went to camps, and women from moderately damaged areas who went to camps, do not recover their assets as well in the long term as those who do not. This suggests that in the medium-term, camps are somewhat effective at assisting people in smoothing consumption, though with regard to assets the effect of going to camps depends on gender.

Lastly, given the heterogeneity of outcomes, I turn to investigate the effects of the natural disaster on inequality. Within highly damaged areas, inequality in real PCE and real assets spiked dramatically immediately in the aftermath of the tsunami. However, in the long term real PCE inequality returned much closer to pre-tsunami levels, and asset inequality declined across the entire region, not only areas directly affected by the tsunami. Long term declines in asset inequality are not surprising in this context, and are consistent both with heavily damaged areas having initially higher asset levels and with housing aid potentially raising asset levels for the poorest in these communities.

This paper makes several key contributions to the literature on the economics of disasters. First, I document the impact of an *unexpected* natural disaster on *real* economic outcomes at the individual level in the long-term. Second, I use uniquely rich longitudinal data to identify heterogeneity in individual outcomes in the long-term. Third, I evaluate the effects of this disaster on the distribution of wealth both *within* directly affected communities and across communities in the long-term.

The remainder of this paper proceeds as follows. Section 2 discusses the context, event, and relevant literature. In Section 3, I lay out the conceptual framework for this paper. Section 4 describes the dataset that I use. In Section 5, I lay out my empirical strategy. Section 6 presents my results and discussion. Section 7 discusses extensions of the research, and Section 8 concludes.

2. Background

2. a. Literature Review

Little previous work investigates the long-term effects of major natural disasters on consumption and wealth in the long run. It is clear that major shocks to consumption and assets have direct links to personal wellbeing, with direct links to health and self-reported wellbeing beyond the obvious negative economic implications, which may have outsized impacts in developing contexts (Seeman et al., 2018. Evans-Lacko et al., 2013). Furthermore, major infrequent economic disasters have a much larger welfare cost than economic fluctuations of smaller size, so understanding the impacts of major natural disasters in both the short term and the long term is of high importance (Barro, 2009).

Much of the literature following natural disasters over a long time frame focuses on aggregate measures of wealth and consumption. This makes it difficult to understand the likely heterogeneity of outcomes among different groups and relevant contributions to the distribution of wealth. This body of work generally suggests that insurance and disaster aid are not enough to smooth financial exposure to risk, and thus natural disasters tend to have negative effects on overall wealth and income. Nonetheless, it is uncertain if these effects persist into the long term (Guimaraes, Hefner, & Woodward, 1993. Schumacher & Strobl, 2011. Cavallo et al., 2013).

However, very recent macroeconomic evidence from Aceh and the Indian Ocean Tsunami suggests that in Aceh, the long-term GDP growth was actually greater in areas that had been flooded when compared to areas that had not been (Heger & Neumayer, 2019). The authors suggest that population changes (mortality amongst children and the elderly, along with migration into Aceh), as well as an acceleration in the structural economic shift away from agriculture and toward services in the areas that were rebuilt, set flooded districts on a new long-term growth trajectory. Their paper noted large rural and urban differences in the pace of post-tsunami growth, with urban areas growing faster (in part because they received aid earlier). However, the paper did not consider the potential role of adjusting for regional price differences in real economic wellbeing and was focused only on aggregate measures.

Given the importance of the distribution of resources to wellbeing in developing contexts, it is important to consider the heterogeneity of impacts of natural disasters and any effects on inequality, which is difficult without microeconomic data.

A notable contrast with the macroeconomic approach to evaluating the outcomes after a disaster is the work of Carter et al. (2007), who document heterogeneity in the effects of Hurricane Mitch on long-term assets in Honduras finding that individuals with less wealth before the hurricane were less effectively able to recover. Their theory is one based on poverty traps – that people with less initial wealth are more likely to be pushed below the point at which it becomes difficult to begin investing in assets and to draw on asset stocks to consumption smooth tasks such as educating family members. However, the work is limited by a small sample size, and is unable to fully investigate the heterogeneity of results in the long term. Other microeconomic literature focuses on the higher vulnerability of lower socioeconomic status populations to natural disasters. This body of work underscores how vulnerability is not just a function of total economic exposure, as the best-resourced individuals in a population would always thus be the most vulnerable, but also is a function of ability to recover, underscoring the ways that lower resource areas tend to be the most directly exposed. This research suggests that, since lower resource populations are less effectively able to recover from exposure to a natural disaster, the uneven vulnerability to natural disasters increases inequality (Adger, 1996; Masozera et al., 2007).

Other microeconomic literature derived from climate shocks due to relative shocks in rainfall and temperature suggests heterogeneity in the impacts of climate shocks on health and economic outcomes in the short run. This literature points towards the importance of consumption smoothing. These works suggest that families that are able to better transfer between households in different villages, or households that have access to credit since they live in banked areas, are better able to smooth consumption to dampen the effects of a short-term weather shock (Burgess, Deschenes, Donaldson, & Greenstone, 2017; Kubik & Maurel, 2016).

Building on the potential heterogeneity in vulnerability to natural disasters and the abilities of different groups to respond, a small body of work examines the effects of natural disasters on inequality.

However, this literature is mixed. Bui et al. (2014) report that while natural disasters in Vietnam have negative economic effects on both directly exposed and non-directly exposed households, they find that household income inequality increases after a natural disaster. In contrast, Keerthiratne & Tol (2018) find that using longer-term data from Sri Lanka, income inequality actually decreases, while expenditure inequality remains the same. Macroeconomic evidence from a longer time horizon, using cross-country data, suggests that natural disasters increase inequality in the 5-year time horizon but the effect disappears in the longer term (Yamamura, 2014).

Beyond the direct wellbeing effects of changes in assets or consumption, changes in prices likely have important effects on real economic wellbeing. Particularly in developing settings, spikes in the price of food can raise the real incidence of poverty dramatically (Beegle, Frankenberg & Thomas, 1999; Frankenberg, Smith & Thomas, 2003; Ferreira et al., 2011). Given that natural disasters can directly affect the supply of food by destroying crops or the infrastructure necessary to transport it, there is potential for natural disasters to have further impacts on real wellbeing by directly impacting prices. The evidence regarding the effects of natural disasters on prices is mixed, however evidence from settings where the impact of the natural disaster affected crops directly suggests high increases in price levels, particularly in the price of rice (Del Ninno et al, 2003; Cavallo et al., 2014). Evidence from Indonesia, but not including Aceh, from the 2004 earthquake suggests that there was a direct relationship between the level of damage sustained in an area and the increase in the price of rice, the staple crop (Kirchberger, 2017). These differential price changes between more and less damaged areas may also play a role in inequality between regions. Despite the potentially important role of prices in real economic wellbeing, none of the cited studies on economic wellbeing consider the price effects of a natural disaster, and their potential for impacting results.

There are several key ways in which an individual or household's economic resilience is likely to have been affected. Households with more accumulated wealth may be able to spend it to smooth consumption, and may be able to sell nonessential assets (such as gold) to replace essential items such as homes to avoid displacement. Households with closer links to family members or communities may be able to smooth resources within their social networks, insulating their consumption from the effects of a negative shock or giving them the resources to rebuild assets. Households with access to credit may also reallocate their consumption from future time periods, and defer purchases of items such as durable goods (Frankenberg, Smith, & Thomas, 2003; Deaton, 1992; Udry, 1994; Townsend, 1994). In the longer term, individuals with greater human capital may be better insulated from labor market shocks. As noted above there may be substantial differences in the recovery trajectories of urban and rural areas (Cutter et al., 2016; Muttarak & Lutz 2014).

2. b. The 2004 Earthquake & Tsunami

The natural disaster studied in this paper is the 2004 Indian Ocean Tsunami. The tsunami resulted from a massive megathrust earthquake in the Indian Ocean, generating waves that impacted shorelines throughout the region. The west coastline of Aceh, a province in Indonesia, was hardest hit. Waves upwards of 30 meters struck Aceh's shore 15 minutes after the earthquake. Approximately 250,000 people along the coastlines of the Indian Ocean were killed, and it displaced more than half a million Indonesians alone.

The tsunami was not expected. Unlike Pacific-Ocean facing communities, for which tsunamis are comparatively common and have associated disaster response protocols, the Aceh province had not seen a tsunami for over 600 years (Monecke, Finger, Klarer, Kongko, McAdoo, Moore, & Sudrajat, 2008). There were, as a result, no warning buoys or disaster-driven urban planning. Exposure to the tsunami itself was dependent on an idiosyncratic function of wave direction, ocean floor topography, land features, and the interactions between wave direction and ocean/land topography. The resulting exposure was thus unexpected and unable to be predicted *a priori*. There were large variations in tsunami exposure – ranging from no exposure to total destruction, in a relatively compact geographical area, the province of Aceh.

These factors enable the tsunami to be treated as a generalizable case study for the impact of unexpected natural disasters. Due to the nature of the tsunami, exposure was orthogonal to pre-tsunami variables of interest, so exposure can be treated as exogenous in our model. This is in contrast to many studies of natural disasters, in which exposure is endogenously related to socioeconomic factors and behavioral responses to avoid exposure (Baker, 1991). In particular, the selection of individuals into pre-disaster evacuation (for events that were foreseen by weather agencies) or migration (in areas that see frequent disasters) on socioeconomic factors and unobserved characteristics makes it difficult to assess and interpret the impacts of a disaster on different pre-disaster demographic groups. By using carefully collected data on the 2004 Indian Ocean Tsunami, we are able to address this challenge and provide unique insight into the outcomes of individuals exposed to a major natural disaster.

3. Conceptual Framework

A large literature investigates the ways in which individuals seek to smooth consumption over time. A starting point for much of the work on consumption smoothing is grounded in the "lifecycle hypothesis," which highlights the role of savings and borrowing to separate the timing of consumption from the timing of income receipts (Modigliani, 1966). Individuals seek to smooth consumption in order to maintain constant marginal utility of consumption over time, taking into account changing needs over the life course, uncertainty and liquidity constraints (Townsend, 1994; Attanasio, 1999; Deaton,1989). Whereas much of the literature has focused on the consumption function, micro-econometric studies in advanced and developing countries have documented that individual and their families adopt a broad array of mechanisms to smooth utility including re-allocating consumption away from deferrable spending and reducing leisure even in the face of dramatic declines in hourly earnings (Frankenberg, Smith, & Thomas, 2003; Browning & Crossley, 2009).

In theory, the declining marginal utility of additional consumption in any period implies that an individual will seek to smooth the flow of utility consumption (taking into account the value of leisure) over time by saving and borrowing. However, their ability to do so is likely constrained by circumstances of the individual, markets, and the nature of the shock. The literature has highlighted the key role of credit markets along with savings and assets that have been accumulated in anticipation of a negative income shock. There is little evidence on smoothing behaviors when credit markets freeze up, earnings opportunities collapse and the value of savings and assets are decimated. This is the context in which I examine the extent of consumption smoothing among people who were living in areas that were directly impacted by damages due to the tsunami, in comparison with behaviors of those in areas not directly affected, many of whom may have actually benefited from the rise in the price of food and housing due to the tsunami. These analyses are complemented with parallel comparisons of the evolution of assets among the same study subjects to build a richer picture of consumption smoothing in the face of a major natural disaster.

3.a. Model

At each point over the life course, t, an individual will choose consumption, C, and leisure demand, L, to maximize the expected value of lifetime welfare, Ψ, conditional on demographic characteristics, A, background, B, an individual specific discount rate δ that can vary over the life course, and tastes, a component of which is invariant (ξ) and a component of which may vary over time (ξ_t).

$$\Psi_\tau = \Psi\{E_\tau \delta_{t\ t-1} U_t(C_t, L_t; A_t, B, \xi, \xi_t)\} \quad t=\tau, \tau+1, \ldots \text{T}. \qquad [1]$$

Choices are constrained by period-specific factors, including a period-by-period time budget constraint that limits the sum of hours of work and leisure, and a lifetime budget constraint:

$$V_T = \left(\textstyle\prod_{t=1}^{T} (1+r_t)\right)V_0 + \textstyle\sum_{t=1}^{T} \left(\textstyle\prod_{t=\tau}^{T} (1+\text{r}_\tau)\right) \{(\lambda_\tau w_t L_t) - (p_t C_{t^*})\} + \left(\textstyle\prod_{t=\tau}^{T} (1+\text{r}_\tau)\right)\varepsilon_\tau \qquad [2]$$

In this case, V_T is the assets at the end of life – this may be positive (bequests), negative (debts) or zero. V_0 is assets inherited at the beginning of life and r_t is the interest rate. Thus, the first term on the right-hand side of [2] is simply the present discounted value of initial assets. The left-hand side of the equation represents asset accumulation. In each period, asset accumulation is the value of the difference between earnings (L_t hours at wage w_t, and a wage shock λ_τ that can deviate from 1) and expenditure (price p_t times spending on consumption goods C_{t^*}). The extent to which total assets in any period can be negative is limited to whatever constraints exist on borrowing. Idiosyncratic shocks to resources enter as ε_τ, and can be positive or negative.

Solving the lifetime inter-temporal resource allocation system yields a period-specific consumption function, C_t, that depends on resources at birth, V_0, the past and future expected values of prices, denoted by the vector $\underline{p}$, wages, $\underline{w}$, interest rates, $\underline{r}$, and shocks λ and ε along with individual-specific preferences ξ.

$$C_t = \text{f}(V_0, \underline{p}, \underline{r}, \underline{w}, \varepsilon, \lambda, \xi) \qquad [3]$$

For the sake of tractability, I ignore changes in leisure demand and assign each individual the average consumption per person in their household. Under the assumptions of the model, individuals will seek to maintain the same level of consumption over time and I focus on the evolution of consumption over time and absorb all time-invariant characteristics into an individual-specific fixed effect, μ, and estimate the model:

$$C_{it}= \beta_0 + \beta_t Y_t + \mu_i + \eta_{it} \qquad [4]$$

Where Y_t is time since the tsunami (measured as an indicator variable for each survey wave), and η_{it} is time-varying individual-specific heterogeneity. The individual-specific fixed effect captures all time-invariant individual characteristics including preferences, pre-tsunami behaviors and experiences as indicated in [3]. For each individual in the study, I document the evolution of period-specific consumption from the year before the tsunami through 10 years after the tsunami to provide evidence on the extent to which exposure to the damage caused by the tsunami is linked to deviations from complete consumption smoothing and to also document the nature of recovery of consumption after the tsunami. I complement [4] with the analogous model for the evolution of resource availability replacing consumption with the value of individual-specific assets.

The tsunami can directly affect the ability of individuals to consumption smooth by having a direct impact on accumulation of resources and the lifetime budget via ε_τ. This may also be a substantial source of heterogeneity amongst individuals in the population, and a driver in part of inequality. ε_τ is likely larger from people who had larger endowments of assets at the time of the tsunami. On the other hand, if the negative ε_τ of the tsunami is small in low asset populations because assets are initially low, it may be the case that positive ε_τ from redevelopment, and in particular widespread housing aid, may in fact lead to asset increases. The tsunami may also directly impact the constraint [2] through shocks λ_τ to the marginal product of labor. This is likely to vary particularly sharply by education, age, and other forms of human capital, but the effect it is not clear *a priori*.

Previous literature has suggested the role of community smoothing, reallocation of leisure across time, and use of credit in consumption smoothing (Townsend, 1994; Frankenberg et al., 2003). Due to the major community-level impacts of the tsunami, it is likely that community smoothing was highly constrained in this context. There was also likely substantial heterogeneity in the ability to utilize other consumption smoothing mechanisms. It is likely that heterogeneous human capital accumulation associated with education levels, gender, urban/rural status, age, and other unobserved individual-specific characteristics are linked to an individual's ability to consumption smooth through reallocation of leisure (Morduch, 1995; Mu, 2006). Furthermore, the extent to which V_T can be negative will be dependent on access to credit or ability to draw on social networks – which may be linked to similar individual-specific factors.

Migration decisions, especially those to refugee camps, are of particular interest in part because a lot of resources are directed to refugee camps in the aftermath of disasters. It has been suggested that migration decisions to new opportunities may be essential components of consumption smoothing in the aftermath of adverse events (Morduch, 1995). Much of the geographical literature notes that the individuals displaced by natural disasters often resettle in more vulnerable areas, and thus make the assumption that post-disaster mobility is an inherently negative outcome (Gray et al., 2014). However, from the perspective of economic wellbeing, it is not clear that migration decisions are inherently negative. Decisions to migrate may affect the constraint through multiple pathways: improved access to credit markets or family members may affect the ability to draw negative V_T, it may enable them to minimize the effect of a shock to wages λ_τ, or it may potentially enable better access to direct sources of aid that could counteract negative ε_τ for movers to refugee camps. The decision to migrate is also likely conditioned on a number of unobserved factors, such as entrepreneurial nature or willingness to move to opportunities.

Given the individual-specific heterogeneity in the constraints on consumption smoothing, and potentially on the direct effects of the tsunami as well, I focus my analyses on this heterogeneity. I will utilize individual fixed-effects in order to control for unobserved time-invariant components that may affect the response to the tsunami, as well as gender, age, education, urban/rural status, and the decision to move to refugee camps.

4. Data

4. a. Dataset

I use data drawn from the Study of Tsunami Aftermath and Recovery (STAR), an ongoing longitudinal study with detailed information on income, assets, education, health, and household composition for individuals and households. Community level data was also collected regarding infrastructure, tsunami aid, community services, and market prices in each community. Specifically designed to assess the impacts of the 2004 Indian Ocean tsunami, STAR built upon a population-representative survey called SUSENAS conducted by Statistics Indonesia in Aceh province and North Sumatra in February 2004. This wave provides population-representative socioeconomic data *before* the tsunami. Individuals interviewed in SUSENAS living in 13 districts along the coast of Aceh were selected to serve as the baseline of STAR. These districts were selected because they were geographically positioned to be at risk of severe exposure to the tsunami, though many parts of the coast were not directly impacted. This provides communities that were directly affected by the tsunami and coastal communities nearby that were not directly exposed.

Annual follow-ups of baseline members as well as co-resident family members occurred in the 5 years following the tsunami, and another follow up occurred 10 years later. Both individual and household-level data are collected in each wave. Every adult in a household was eligible to be interviewed, and information about every child was collected from a parent. Due to careful attention from the field team, at least 98% of survivors have been interviewed post-tsunami. Within my target sample of individuals who were between the ages of 15 and 65 at the baseline interview, 96% of surviving individuals were re-interviewed in the 10 year follow-up, and upwards of 97% were re-interviewed at least once after the tsunami. This includes individuals who moved to locations in other parts of Sumatra, Java, and other islands in Indonesia as well as movers to Malaysia and Singapore. Follow-up of movers is critical, since in the aftermath of the tsunami a large portion of people moved from their original household locations. Claims about population representative attributes may not be accurate in panel surveys in which movers are not tracked, since observed and unobserved characteristics may systematically differ for movers and non-movers (Thomas et al., 2001).

4. b. Tsunami Exposure

Individuals are stratified into three categories of exposure to the tsunami – as living in heavily damaged, moderately damaged, and not directly affected communities *at the time of the tsunami*. This was done using several biophysical measures from satellite imagery, in coordination with GPS measurements collected in each study site. We started with a measure constructed by comparing satellite imagery from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) from the week before the tsunami to images collected three days after. The proportion of land cover that was changed to bare earth was manually assessed for a 0.6km$_2$ area over each GPS point. This information was supplemented with damage estimates from remotely sensed imagery and prepared by the USGS, USAID, Dartmouth Flood Observatory, and the German Aerospace Center (Gillespie et al., 2009). In each community, interviews with local leaders were conducted who provided their own assessments of destruction to the built and natural environment. Third, survey field supervisors completed a questionnaire in each community that detailed damage due to the tsunami and earthquake based on their own direct observations (Frankenberg et al., 2011).

This information was used to construct the three categories of damage exposure at the time of the tsunami in each of the over 600 communities included in the STAR pre-tsunami baseline. The classification has also been cross-validated with data on community-specific mortality from the tsunami. In heavily damaged communities mortality for primary adults was high, and very close to zero in moderately damaged communities. Communities that were not directly affected sustained no tsunami-related death. The classification has also been cross-checked with administrative data collected by Statistics Indonesia and the measures display high levels of concordance. Our STAR measures of damage classify 96 baseline communities as heavily damaged, 276 as moderately damaged and the remaining 290 as not directly affected. This measure is linked to individuals based on their place of residence at the time of the pre-tsunami baseline.

4. c. Measures of economic wellbeing

Household Per-Capita Expenditure (PCE)

Household expenditure in STAR utilizes a "short-form" consumption module that takes approximately 30-40 minutes to administer. Questions are asked about a series of commodity categories; for each item, the respondent is asked first about money expenditures and then about the imputed value of consumption out of their own household production or provided in kind. Expenditures are reported for the previous week for food items (such as rice, cassava, tofu, tempe, etc). Respondents that produce their own food are asked to value the amount consumed in the previous week. For non-food items, a reference period for the previous month is used for some (such as electricity, water, fuel, transport), and the reference period for other goods is a year (for items such as clothing, medical costs, and education). Respondents are asked about rental costs if they are renting, or for the estimated rental equivalent for those who are not. Since the distribution of per-capita expenditure tends to be right-skewed, the natural log of PCE is used as the primary outcome in this paper.

Household Assets

STAR contains information on the value of assets that are associated with family businesses and, in a separate module, the value of all nonbusiness assets owned by the household. These are divided into ten categories that include property; saving, stocks, and loans; jewelry; household semidurables; and household durables. From these modules, it is possible to then construct a measure of a household's accumulated wealth. Household assets were not part of the questionnaire conducted by Statistics Indonesia that serves as the baseline for the study. For the baseline wave, a similar questionnaire to the other waves was used, asking individuals to retrospectively assess their pre-tsunami assets and value from a year before. Assets, similar to PCE, lie on a right-skewed distribution, so the natural log of assets is used for analysis in this paper.

Since assets, unlike PCE, were constructed retrospectively, there is a concern that individuals who lost significant assets may be prone to overstate their losses, and thus the initial value of their assets. As a result, the change in assets from the pre-tsunami baseline to the year after the tsunami -

when assets were assessed at the time of interview – is likely overstated, and it is not possible to discern the portion of initial asset losses that represent retrospective reporting error. However, assets were assessed at present value with the same instrument in all waves after the baseline.

Prices

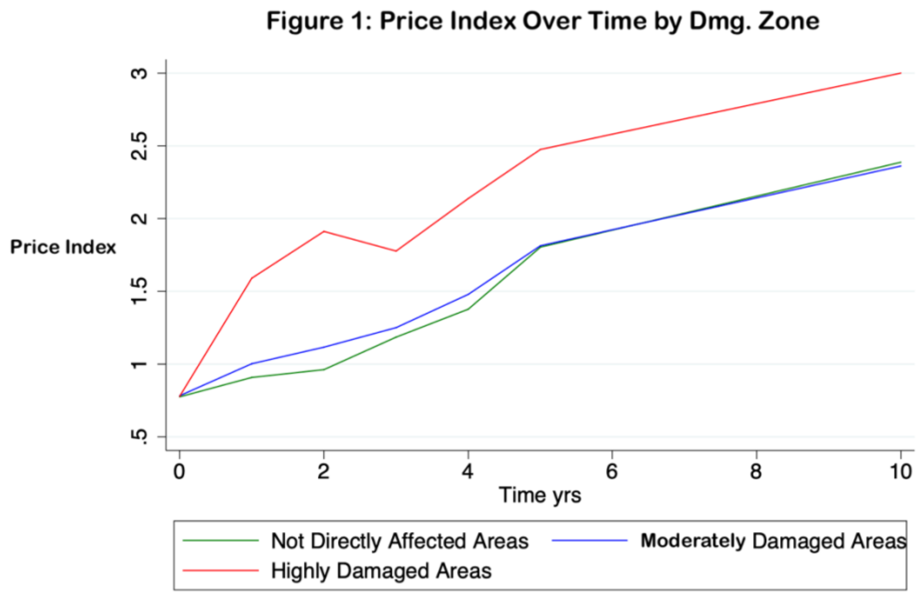
Given concerns about the direct effects of exposure to the tsunami on local prices, *kabupaten* (regency, one level below province)-level price deflators were constructed specifically for this paper. Within each *kabupaten*, price indices were constructed separately for each of the three damage levels. Starting with the first post-tsunami wave, the 1 year wave, enumerators completed a community survey in each baseline community that included detailed collection of local area price data. This is very unusual for household survey data and was implemented because prices were likely to diverge across communities precisely because of the damage from the tsunami. In each community, up to three local markets and or stores were visited, and in each one, enumerators obtained prices for 70 major food items, including the key staple, rice, as well as meat, fish and vegetables. All prices were standardized to a pre-determined weight, and, when necessary, goods were weighed by the enumerator. In addition, three community expert informants in each enumeration area were asked to provide information on the prices of 27 items including electricity, fuel, transportation, health center costs, rent of various items, building materials, and specific types of clothing. These prices were also standardized to be comparable. The median prices for each of these 97 goods was taken within all communities in each *kabupaten* that had sustained the same damage exposure level, creating *kabupaten*-exposure level median prices of each good.

Each household was also asked about their expenditures on a range of categories: housing, utilities, education, health, clothing, durable goods, transportation, food (divided into rice, dairy, vegetables, cereals, and other foods), insurance, alcohol and tobacco, personal services, durable goods, housekeeping/home improvements, and taxes. From this information, household level expenditure shares were created for each category. Mean expenditure shares for each category were then calculated at the *kabupaten*-exposure level. From the above market and informant prices, "baskets" of goods were created for each expenditure share category. Within each expenditure share category, the price of the cumulative basket of goods was multiplied by the expenditure share, and summing across expenditure share categories, an index was created for the price level, standardized to the price level in a not directly affected *kabupaten* in Banda Aceh, the capital city of Aceh.

The median price levels calculated in each *kabupaten*-exposure level were then assigned the median interview date for a given *kabupaten*-exposure level. Based upon the interview dates of a household, and the given price points between waves, the price level for a given household at its specific interview date was interpolated exponentially and then assigned to the household.

Price level data at this geographically precise of a level is not available outside of this study. However, Statistics Indonesia tracks the consumer price index in Banda Aceh, the capital city. Within the city of Banda Aceh, the price index generated for this study closely tracks the one generated by Statistics Indonesia for the first 5 years after the tsunami. However, it diverges and reports lower inflation than Statistics Indonesia at year 10. The Statistics Indonesia data reports 70% higher price levels ten years after the tsunami than at the 5 year point after the tsunami. The price index generated from this study reports 15% higher price levels at the 10 year timepoint than the 5 year timepoint. The results reported in this study are similar, albeit with substantial additional reductions in real assets and PCE at the 10 year time point, if the price index is inflated to match the Statistics Indonesia price levels while maintaining the spatial variation calculated between *kabupatens* and damage zones.

Looking at the trajectories of the price indices over time, it is quickly obvious why such detailed price data was necessary (Figure 1). The trajectory of the price indices diverges sharply in the years following the tsunami, then follows similar trends in the long term. In Figure 1, Time 0 is the pre-tsunami baseline, “Time years” denotes the amount of years that have then passed since the tsunami.



It is also important to note that in the 6 years leading up to the 10 year follow up, all damage zones see substantial declines in real assets and the real PCE despite nominal increases. While initially surprising, this result is confirmed by data on subjective economic wellbeing asked of each individual using an adaption of the Cantril ladder question (Appendix 1). Each individual is asked to place themselves on one of six rungs of a ladder where the poorest person in the society is on the bottom rung and the richest person is on the top rung. This data shows major declines in self-reported economic wellbeing in the 6 years leading up to the 10 year follow up, which is consistent with measured declines in real wealth and real PCE.

Camp Migration

In order to consider the role of behavioral responses to the tsunami on long term outcomes, individuals were asked about their migration histories. This included information on the specific location, as well as length of time spent in, a given site. From this information, an indicator variable was generated, which takes the value of 1 if an individual spent any time in a refugee camp and 0 otherwise.

Urban/Rural

Urban and rural status is generated as an indicator variable for each enumeration area. These classifications are drawn from data from Statistics Indonesia, which classifies enumeration areas based upon population density, percentage of agricultural households, and density of “urban” facilities (such as senior high schools, hospitals, cinemas, and banks). These classifications are identical to the classifications used in the most recent Indonesian Censuses.

Coefficients of Variation

Coefficients of Variation (CVs) are mean-independent, population-size independent, and easily decomposed, making them ideal choices for measures of inequality where levels of consumption and assets are changing over time (Shorrocks, 1980). CVs were calculated for real PCE and real assets in each wave for the entire survey population as well as within damage zones. For each of these populations, CVs were calculated by dividing their standard deviation by the mean of that sample. Since the populations had large and small outliers, trimmed CVs were calculated with the top and bottom 5% of each sample removed in order to address extreme outliers in the data.

Demographic variables

Indicator variables for *Years of Education* generated from a continuous years of education variable that ranges from 0-16 years, measuring education at the time the tsunami struck. These education categories include 0-6 years (the excluded term in regression models), 7-12, and 13+ years of education.

Indicator variables for *age at the time of tsunami* were generated using a continuous variable that showed the age of every individual in the sample at the time the tsunami struck. Individuals below the age of 15 at the time of the tsunami were not included in the sample. These age categories were 15-30 years old (the excluded term in regression models), 30-45 years old, and 45+ at the time of the tsunami.

Tsunami exposure indicators were made in accordance with the classification system described above. Indicators for heavily damaged, moderately damaged, and not directly affected (excluded in models) were used.

Table 1 reports descriptive statistics for individual characteristics, stratified by damage zone. The highly damaged areas contain large parts of the province’s capital city, Banda Aceh, and unsurprisingly tend to be both more urban and slightly more highly educated than the other damage zones. Similarly, pre-tsunami real assets and real PCE are higher in highly damaged areas. However, controlling for demographic differences between damage zones, the differences between real assets and real PCE across damage zones is no longer as large, and is only significant with regards to real PCE and moderately damaged zones (Appendix 2). Prior to the tsunami, not directly affected, highly damaged, and medium damaged areas have very similar price levels.

5. Empirical Strategy

The descriptions, above, of economic trajectories across the three damage zones are informative about aggregate change in the aftermath of the 2004 Indian Ocean tsunami. The descriptions do not, however, provide evidence on the evolution of well-being of individuals and they are silent with respect to heterogeneity in these pathways across population sub-groups. My empirical research is designed to provide new evidence of these questions by exploiting the individual-level information collected by tracing the trajectories of economic wellbeing of a population-representative sample of survivors of the tsunami who were interviewed before the disaster and have been tracked for 10 years after the tsunami.

A goal of this research is to identify the causal impact of exposure to a large-scale natural disaster on economic well-being in the short and longer-term. This is not straightforward. The initial shock to economic wellbeing is plausibly exogenous since the tsunami was completely unanticipated and the communities that were damaged depended on idiosyncratic features of the topography of the land and sea bed (Frankenberg et al, 2012). However, as explained in the discussion of consumption smoothing behaviors, it is not plausible to interpret post-tsunami trajectories for different individuals as indicative of causal impacts. Namely, the post-tsunami evolution of wellbeing is a complex combination of the shock itself, resource availability at the time of the tsunami and characteristics of individuals including their willingness to take on risk, attitudes towards the future, entrepreneurial skill and propensity to take on new challenges. To the extent that all of these characteristics are fixed for an individual, it is possible to identify the causal effect of the tsunami by estimating models of economic outcomes that include individual-specific fixed effects. The trajectory of economic outcomes, y_{it}, is traced out over time from the tsunami, Y_t, taking into account all individual-specific characteristics that are fixed, μ_i:

$$y_{it} = \beta_0 + \beta_1 Y_t + \mu_i + \eta_{it} \qquad [5]$$

where η_{it} reflects unobserved time-varying individual-specific heterogeneity. Each time point is measured with an indicator variable for each survey wave to provide a parsimonious semi-parametric functional form that captures change post-tsunami. This is done for all damage zones. The pre-tsunami baseline is excluded and absorbed in the intercept, β_0. Estimates of the coefficients β_1 are interpreted as tracing the evolution of economic wellbeing relative to the pre-tsunami level, adjusting for all individual-specific fixed characteristics. They can be interpreted as reduced form estimates of the causal impact of the tsunami. Estimation of a structural model that takes into account time-varying characteristics and behavioral choices of individuals and the economic environment in which they are living is not possible with the data collected in STAR. All models are stratified by damage zone of the respondent. All variance-covariance matrices are estimated taking into account clustering of the baseline survey and arbitrary forms of heteroscedasticity (Huber, 1967).

The second objective of this work is to examine heterogeneity of the economic trajectories within sub-groups of the population. Given the heterogeneity of the health impacts of traumatic exposure based upon gender, age, and educational access, and the differential abilities of individuals of different ages and education levels to respond to changes in the labor market, I examine the distribution of the tsunami's effects across education levels and age. Let V_i represent vectors of indicator variables representing pre-tsunami baseline individual characteristics, such as gender, age, education, or urban status.

Model [5] is extended to include interactions with baseline characteristics:

$$y_{it} = \beta_0 + \beta_1 Y_t + \beta_2 V_i{*}Y_t + \mu_i + \eta_{it} \qquad [6]$$

where η_{it} is the error term. Robust standard errors are used for this estimate. The objective is thus to estimate β_2, which would be interpreted as the difference in the effect size at that point in time, relative to the pre-tsunami level for an individual in that demographic group relative to the excluded group, adjusting for all individual-specific fixed characteristics. Since demographic characteristics are fixed to their status prior to the tsunami, I consider them external to tsunami exposure. While further behavioral responses after the tsunami, such as rural-to-urban migration, are of great interest, this paper focuses on pre-tsunami characteristics, and only investigates refugee camp status (which I do not consider exogenous) as a behavioral response. All models are stratified by respondent gender and damage zone.

6. Primary Results, Discussion

6. a. Individual Fixed-Effects Models

Table 2 presents individual fixed-effects models on the natural log of real per capita expenditure and the natural log real assets. As noted previously, prior to the tsunami, the highly damaged areas had substantially more assets and expenditure than moderately and not directly affected areas. Real PCE fell significantly in all areas in the year after the tsunami (Table 2, Columns 1-3), surprisingly falling as far in non-directly damaged areas as it did in heavily damaged areas. However, the effect on real PCE was not as large in moderately damaged areas. In highly damaged areas, this reflects a surge in nominal PCE that is accompanied by a larger spike in price levels, whereas in not directly affected areas, this reflects a decline in nominal PCE. By the second year real PCE had mostly recovered in moderately and not directly affected areas, and it continued to recover in the third year to within 5% of pre-tsunami levels. However, in heavily damaged areas real PCE was still over 26% lower in heavily damaged areas by the third year. In the 5th year and by the 10 year follow up, real PCE fell in all regions, but the decline from pre-tsunami levels was significantly greater in high damage regions than in moderately and not directly affected areas.

Thus, while the initial impacts of the tsunami were fairly similar across damage zones, there were significant differences in recovery trajectory. These results are generally paralleled by similar findings using subjective economic wellbeing (Appendix 1). Despite initially higher PCE, heavily damaged areas not only suffered a larger decline in PCE, but had lower overall real PCE than not directly damaged and moderately damaged places as time went on. From this standpoint, heavily damaged areas clearly did not recover. On the other hand, moderately damaged areas had a smaller reduction in PCE in the year after the tsunami than both not directly damaged and highly damaged areas. The drop from pre-tsunami log PCE was smaller in moderately damaged areas than in not directly affected areas at all time points, including in the long term, suggesting moderately damaged areas did comparatively well in the long term. This may potentially be due to the large size of the reconstruction effort in the damaged areas, which may have helped moderately damaged areas (which were not as directly damaged by the tsunami) recover.

Unsurprisingly, immediately after the tsunami, real assets fell dramatically in highly damaged and moderately damaged areas, increasingly slightly in areas not directly affected (Table 2, columns 4-6). However, as discussed previously, individuals who lose substantial assets are likely to overstate the value of their losses. As a result, it is uncertain what proportion of asset losses from the baseline to one year post-tsunami is due to retrospective overstatement. In highly damaged areas, from this low point, real assets continued to increase steadily until 3 years after when they reached their highest point before declining slightly and rising again to the 10 year follow-up. At their highest, 3 years after exposure to the tsunami, however, real assets in highly damaged areas had still declined over 35% from their initial reported value. On the other hand, not directly affected and moderately damaged areas also had steady growth in asset values after the first-year post-tsunami. Three years out they had increased 26% over their initial starting point. By the 10 year follow up, real asset values in not directly affected areas had risen to 31% over the pre-tsunami baseline, and in moderately damaged areas had risen to nearly 25% greater than the baseline. In summary, for real assets, by 10 years out, individuals in heavily damaged areas had not recovered their assets from prior to the tsunami, and individuals in moderately damaged areas had not recovered quite as well as individuals from not directly affected areas.

These results contrast with the results using nominal PCE or nominal asset values, underscoring the role of the price effect in producing negative economic outcomes for people who lived in high damage areas. Looking at nominal PCE, it fell significantly in not directly affected and moderate damaged areas in the year after the tsunami, but jumped significantly in high damage areas (Appendix 3, Columns 1-3). Combined with the spike in prices, this increase in nominal PCE may be consistent with price gouging in the aftermath of the tsunami, rather than a real improvement in economic wellbeing by raised consumption. In the long term, all damage zones have substantially increased nominal PCE, and heavily damaged areas have significantly higher PCE than other damaged areas. This is again in contrast with the price-adjusted real results. Looking at nominal asset values, in all damage zones asset values dramatically increased at the 10 year follow up (Appendix 3, Columns 4-6). Nominal asset values fell in the year after the tsunami in heavily damaged areas, while nominal asset values increased in both not directly affected and moderate damage areas, whereas accounting for prices, asset values fell in moderate damage areas. In the long term, while the log of nominal asset values did not rise as much in high damage areas, heavily damaged areas had substantially raised the value of nominal assets. This is in stark contrast with the results accounting for price changes.

These results build on the macroeconomic evidence from Aceh (Heger & Neumayer, 2019), which suggests that affected provinces may do better than unaffected provinces in the long run. However, this data did not adjust for price levels, which may contaminate results. Though the conclusions of previous work still may be true at the macroeconomic level, the aggregate evidence misses substantial heterogeneity of exposure within affected provinces. *Individuals* exposed generally do not fare as well in the long term in real terms as individuals who were living in nearby, but not directly affected areas.

With the core results established, I now turn to investigating the heterogeneity of these impacts along dimensions likely to affect economic wellbeing as predicted by the conceptual framework. Using longitudinal individual-level data, I will investigate how recovery trajectories (or lack thereof) may vary by gender, age, education, and urban/rural status at baseline before the tsunami.

6. b. Heterogeneity of Impact

Gender

Looking at expenditure, the trajectories of male and female real PCE in the aftermath of the tsunami are similar, which is likely due in large part to co-residence among many males and females (Table 3, Columns 1-3). They both lose similar proportions of PCE in the aftermath of the tsunami across all damage zones. By the second year after the tsunami, males who were living in heavily damaged areas start to see somewhat better recovery than females. This disparity continues to expand over time, and by the 10th year after the tsunami, males have recovered approximately 10% more of their pre-tsunami PCE than females who were living in areas heavily damaged by the tsunami, and have recovered approximately 4% more real PCE than females in not directly affected and moderate damage areas.

With regard to real assets, the trajectories of males and females diverge more starkly than they do for real PCE. The male/female difference immediately after the tsunami is not significant in moderately damaged areas and those not directly affected. In heavy damage exposed individuals, however, males lose 18% more real assets than females in the year after the tsunami. While this difference disappears in the following years after the tsunami, by the 10 year follow up males still have lost over 13% more asset value than females in heavily damaged areas, and do not accumulate assets as quickly in the other damage zones. These differences, particularly in the immediate aftermath of the tsunami, may reflect previously documented differences in types of wealth men and women tend to hold. In Indonesia in particular, women hold substantial wealth as gold, which may have been less likely to be immediately damaged by the tsunami.

Age

Given the differences in trajectory between males and females, the remaining regression results investigating heterogeneity of individual characteristics are all presented stratified by gender. Amongst females, there were no significant differences in PCE changes across age groups in the years immediately after the tsunami (Table 4, Columns 1-6). Among women who were exposed to heavy damage, starting in the 4th year after the tsunami, women in the middle age category (age 30-45) had smaller reductions in real PCE from the baseline than younger women. By 10 years after the tsunami, heavy-damage exposed women in the older age categories experienced significantly less decrease in real PCE form the baseline than did younger women. This remains true to a lesser extent, amongst women who lived in moderately damaged areas or areas not directly exposed. Amongst men who were heavily exposed to the tsunami, there were no significant differences in trajectory by age. However, in moderately damaged areas and areas not exposed directly to the tsunami, older men had significantly larger reductions in real PCE than younger men. This is in contrast with the result for women, however the comparative results between heavily damaged areas and the other damage zones is similar between men and women. Among both genders, the older age indicators were less negative in magnitude in high damage zones than in the lower damage areas.

For males, older males had significantly smaller losses of assets immediately after the tsunami than did the younger population (Table 4, Columns 7-12). While age effects are initially absent in women, women in the middle age category accumulate assets most rapidly in the years after the tsunami in areas not directly exposed and in moderately exposed areas. Among men who were heavily exposed to the tsunami, men in the middle-age category see significantly smaller decreases in assets in the years following the tsunami, and these effects persist into the 10 years follow up. At the 10 year follow up, the oldest category of males also see a similarly mitigated effect. In areas that were not directly affected or moderately damaged, men in the middle and oldest age groups do significantly better over time. Men who were in the middle-age category who were not heavily exposed to the tsunami appear best able to accumulate assets in the aftermath of the tsunami.

Education

In the immediate aftermath of the tsunami, there were not significant differences in the evolution of real PCE by education level (Table 4, Columns 1-6). After 4 years after the tsunami, however, it is clear that the most highly educated individuals faced a larger percent reduction in real PCE than lower educated individuals, regardless of damage zone. It is clear that the most highly educated individuals did not regain their baseline real PCE.

In the first year after the tsunami, more highly educated males who were heavily damage exposed had a smaller percent decline in real assets than those who were in lower education categories. This initial effect is not present in females (Table 4, Columns 7-12). Over time, however, more highly educated males and females in both moderate and high damage zones experience disproportionately negative effects to their real assets. By the ten year follow up, more highly educated women in all damage zones have disproportionately negative trajectories of real assets. Amongst males, by the ten year follow up, the education indicators are not significant in men who were heavily damaged exposed. However, the high education indicator is significant in those who were moderately exposed, and the middle-education indicator is significant and negative for males in all damage zones. It appears that middle-educated men and women, and highly educated women were least effectively able to re-accumulate assets in the aftermath of the tsunami. Middle and highly-educated males in heavily damaged areas experienced disproportionately negative effects on asset accumulation in the mid-term, but these effects dissipate in the long term.

These results contrast somewhat with expectations from previous literature. Based on previous work, one may expect higher education and human capital individuals to be better able to take advantage of opportunities and consumption smooth in the aftermath of the tsunami (Carter et al., 2007). However, this evidence suggests that while higher education individuals may have been less vulnerable in absolute terms, their trajectories of recovery are worse than for lower education individuals.

Urban/Rural

For the natural log of real PCE, urban areas had substantially more negative effects of heavy damage exposure in the short and long term than rural areas – which still saw large negative effects of tsunami exposure (Table 5, Columns 1-6). In the year after the tsunami, there was no distinguishable effect of urban or rural status in moderate damage areas or not directly affected areas, however by the 3rd year after the tsunami, the trajectories of urban and rural areas begin to diverge, and urban areas have significantly larger percent PCE decreases than rural areas do in the long-term.

Looking at the natural log of real assets, in the year after the tsunami, urban males who were heavily damage exposed have less-negative impacts of exposure, and there are no urban/rural differences amongst females or males in other damage zones (Table 5, Columns 7-12). After the first year, the trajectories of the highly damaged areas and the other damage zones diverge. In rural areas, for moderate damage areas and areas not directly affected, assets generally accumulate slowly over and beyond baseline assets. However, urban areas do not accumulate assets as effectively, with negative interaction terms that functionally offset the gains being accumulated in rural areas. In heavily damaged areas, in the medium term a few years after the tsunami, urban areas maintain larger percent decreases in real assets than rural areas, but by the 10 year follow-up males have eliminated this gap while females have not.

Overall, rural areas are better able to recover more effectively than urban areas in terms of both assets and PCE. In non-heavily damaged areas, while there are no differences in the initial impact of the tsunami, the recovery trajectories in the long-term differ substantially between urban and rural areas. With regard to real assets, urban and rural males have no differences in effect over the long term, but the negative effects of the tsunami on women's assets are nearly exclusively concentrated in urban areas.

This evidence suggests that while the impacts of the tsunami in the short term were similar in urban and rural areas, in the long term, rural areas generally fared substantially better than urban areas. These individual level results contrast with the conclusions from the macroeconomic evidence, which suggests faster rates of growth in urban areas rather than rural areas.

6. c. Moving to camps

One of the fundamental questions in disaster response is the extent to which individual decisions and aid affect outcomes in the long-term. While the individual fixed-effect captures propensity to move toward other opportunities that may be related to the decision to move to a refugee camp, to the extent that migration behaviors are related to the tsunami's aftermath, the decision to move to a camp cannot be considered entirely exogenous. I investigate the outcomes in the long term of individuals who spent time in a refugee camp in the aftermath of the tsunami (Table 6). Since very few individuals from areas not directly affected by the tsunami went to refugee camps, I only include analysis of moderately and highly damaged zones.

Looking at real PCE, in the immediate aftermath of the tsunami there are no significant differences between those who went to camps and those who did not. In the medium term after the tsunami, in highly damaged areas, individuals who went to camps had a smaller negative effect on real PCE than those who did not. This effect persists until 5 years after the tsunami, but dissipates 10 years out.

With regard to real assets, individuals who went to camps lost substantially more assets immediately after the tsunami than those who did not. This is unsurprising, as individuals who lost homes likely lost substantially more assets, and this result is consistent with previous evidence on migration after the tsunami (Gray et al, 2014). In the long term, this effect disappears for women in heavily damaged areas – women who went to camps and women who did not have indistinguishable declines in assets in the long term. This is in contrast with results for men, and for women and men in moderately damaged areas. Men who went to camps have significantly greater percent declines in assets in the long term than those who did not. In moderately damaged areas, the negative interaction term for those individuals that went to camps flattens the real asset gains accumulated over time by those who did not go to camps.

This evidence suggests that individuals who went to camps were effectively able to moderate the effects of the tsunami on real PCE. The camps had particularly success supporting consumption smoothing in the short-to-medium term. Given that the individuals who went to camps were initially lower-resourced, harder hit by the tsunami, and likely had unobserved factors such as lack of nearby family that made them more vulnerable to the disaster, their similar real PCE compared to individuals from the same damage zones who did not go to camps is positive. However, the tsunami's heavy impact on the assets of individuals who went to camps remains persistent for most groups in the long term, though the gap does close with individuals who did not go to camps over time. However, in the long term, women from heavily damaged zones who went to camps were indistinguishable from those who did not in the long run.

6. d. Inequality

The large changes in real assets and real PCE raise questions about the potential effects of the tsunami on the distribution of wealth. Using coefficient of variation to measure inequality, PCE inequality in highly damaged areas dramatically increases by over 50%, one year after the tsunami, and increases more mildly in moderately damaged areas. Inequality in highly damaged and moderately damaged areas both then converge more closely to inequality in not directly affected areas by the 10 year follow up. However, inequality in all damage areas had elevated slightly from the pre-tsunami baseline by the 10 year follow up, though not to the same extent as immediately after the tsunami. These results are similar in the trimmed and untrimmed samples (Table 7, Columns 1 and 2). Looking at real assets, inequality in not directly damaged areas increased immediately after the tsunami in the un-trimmed sample, but then declined in both samples consistently over time, suggesting persistent declines in inequality. In highly damaged areas, inequality spiked dramatically in the aftermath of the tsunami, and then declined in every wave after the tsunami (though with smaller changes than in areas that were not directly affected). Overall, asset inequality declined in the long term from the first year after the tsunami in both affected and unaffected areas (Table 7, Columns 3 and 4).

Looking at inequality across the entire sample, PCE inequality spiked one year after the tsunami, then declined substantially from this point in every wave of the survey afterwards. At the 5 and 10 year follow ups, it appears as though PCE inequality had stabilized slightly higher than it initially was before the tsunami. In contrast, asset inequality initially spiked after the tsunami, but then fell dramatically in the years after and continued to fall, finishing significantly lower than it initially was. This is unsurprising at a damage zone level, given the initially higher assets of highly damaged areas that did not recover fully. However, other forces may also have been at work. Housing aid and reconstruction, for example, may have substantially increased the assets of the poorer individuals in the sample.

This is also consistent with evidence at the individual level. As shown above, more educated individuals who were likely of higher socioeconomic status before the tsunami, bore a disproportionate portion of the exposure's effects. I address this explicitly in Table 8, with interaction terms for being in the top and bottom quintiles of baseline PCE and assets, respectively. These results explicitly demonstrate that in terms of both PCE and assets, those initially in the top quintile fare disproportionately worse. Those in the bottom quintile actually appear to likely have done the best comparatively. The bottom quintile of both PCE and assets accumulates positive increases in real PCE and assets across *all* damage zones, which is not the case for the remainder of the population. This may be due, in part, to large distribution of aid in the aftermath of the tsunami. Financial grants were the same regardless of pre-tsunami economic status, and housing aid was precisely standardized, thus likely benefitting the poor proportionally more than the wealthy (Da Silva & Batchelor, 2010). This would be consistent with observations from the first year after the tsunami, where individuals from the bottom quintile in highly damaged areas see the largest boost in PCE. However, it appears that in the long term this effect does not persist. For both real PCE and real assets, in the long term individuals in damage zones not directly affected or only moderately damaged perform comparatively better than those in heavily damaged areas. These results are inconsistent with previously discussed theories about poverty traps in the aftermath of a natural disaster. Since in the long term, individuals who are lower socioeconomic status tend to recover more effectively, it does not appear that constraints consistent with poverty traps were holding back recovery.

7. Future Extensions of Research

There are several avenues for future work that would likely be productive. One important avenue includes use of different asset classes in the STAR data in order to investigate smoothing mechanisms. STAR contains individual level asset ownership of items such as gold, which may be easier to liquidate to smooth consumption, and property, which may be more difficult to liquidate.

Along the same lines, it is likely possible to investigate the distribution of housing aid in the aftermath of the tsunami. This is likely one major source of the asset increases I observe among the poor in Aceh, and investigating the role of housing aid specifically in asset accumulation as well as further investigations into consumption would be very productive and would have direct policy implications.

One of the key determinants of consumption smoothing that this research does not directly address has to do with wages and hours worked. In the conceptual framework, these are clearly important components of consumption. Variations in wages and the ability to work additional hours (or any hours) is addressed tangentially in this research, but further work directly investigating these components would be highly valuable. Along similar lines, this paper's conceptual framework ignores changes in demand for leisure. While this is difficult to address as it would involve estimation of shadow wages, it is something that could potentially be a useful line of research. Based on the results that lower education individuals tended to more effectively recover previous consumption, this suggests that economic conditions in the aftermath of the tsunami were more favorable than before to people with lower human capital. This can be tested directly with further investigation.

8. Conclusion

Understanding the long-term economic impacts of major natural disasters on individuals is only set to grow in importance as natural disasters grow more frequent. Effective recovery in the long term will require robust understanding, across multiple economic dimensions, about what individuals fail to recover without significant assistance. This project helps understand how people respond to a major natural disaster and their recovery processes, contributing evidence that can help inform policies of post-disaster assistance.

Using panel household survey data from Indonesia, I find evidence to suggest that with regard to both real PCE and real assets, individuals in heavily damaged areas did not recover their pre-tsunami levels of real PCE and real assets. Individuals who were living in moderately damaged areas at the time of the tsunami do substantially better. I also document heterogeneity by gender, age, education, urban/rural status. These results are significantly different from the results for nominal assets and nominal PCE, underscoring the importance of the price effect that results from disaster exposure.

I also find evidence to suggest that individuals who went to refugee camps were more effectively able to consumption smooth in the medium term, though these effects do not persist into the long term. However, I find that men in both high and moderate damage zones, and women in moderate damage zones, experience long term negative effects on asset accumulation, which reflect in part substantially larger initial losses of assets. While these are not causal results, they suggest that the refugee camps were effectively able to assist consumption smoothing temporarily, and further assistance could work to help individuals re-accumulate disproportionately high asset losses.

Lastly, this paper investigates the effects of tsunami exposure on inequality. Immediately after the tsunami, inequality spiked across the board on both economic measures. However, in the long term only mild increases in PCE inequality are recorded. Over the long term, asset inequality declined substantially in heavily damaged areas. These results are consistent with the general heterogeneity of results suggesting that individuals of lower SES were able to recover better than individuals of higher pre-tsunami SES.

These results contribute meaningfully to the literature on the effects of natural disasters. These results provide causal evidence on the long-term prospects of individuals who were exposed to a natural disaster, and highlights important heterogeneity that is lost from the macroeconomic approach. This evidence takes into account price effects, and underscores the importance of doing so. Without taking into account of price effects, this paper would have substantially understated the real effects of the tsunami. Lastly, this paper offers evidence that levels of inequality, particularly in assets, were greatly affected by exposure to the tsunami and following aid process. This research underscores the fundamental importance of carefully designed long-term research that can meaningfully understand the effects of a natural disaster over the course of an individual's life.

Table 1: Characteristics of Longitudinal Study Subjects at Pre-Tsunami Baseline

		[1] Non-Damage	[2] Med Damage	[3] High Damage
Male		0.474	0.479	0.502
		(0.00443)	(0.00458)	(0.00868)
Education at the time of Tsunami				
	0-6 Years	0.385	0.428	0.318
		(0.00433)	(0.00454)	(0.00809)
	7-12 Years	0.558	0.513	0.551
		(0.00442)	(0.00458)	(0.00864)
	13+ Years	0.0603	0.0602	0.133
		(0.00211)	(0.00218)	(0.00589)
Age at the time of Tsunami				
	15-30 Years	0.421	0.444	0.438
		(0.00438)	(0.00455)	(0.00865)
	30-45 Years	0.332	0.335	0.353
		(0.00445)	(0.00468)	(0.00916)
	45+ Years	0.217	0.216	0.207
		(0.00391)	(0.00411)	(0.00783)
Urban		0.225	0.288	0.492
		(0.00401)	(0.00459)	(0.00990)
ln real PCE at the time of Tsunami		12.90	12.87	13.05
		(0.00584)	(0.00627)	(0.0116)
ln Real Assets at the time of Tsunami		9.568	9.697	10.59
		(0.0150)	(0.0150)	(0.0276)
Went to Refugee Camp		0.0783	0.304	0.590
		(0.00245)	(0.00427)	(0.00864)
CV% lnPCE		0.0447	0.0457	0.0427
# of Individuals		19,501	21,218	6,312

Note: Robust Standard Errors in Parentheses
All Surviving Respondents who were Interviewed at Baseline

Table 2: Evolution of Real PCE and Real Assets by Damage Zone

	[1]	[2]	[3]	[4]	[5]	[6]
		ln(Real PCE)			ln(Real HH Assets)	
VARIABLES	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage
Constant (Baseline)	12.92	12.87	13.03	9.620	9.606	10.47
	(0.00572)	(0.00608)	(0.0124)	(0.00999)	(0.0110)	(0.0204)
1 Year	-0.334	-0.250	-0.332	0.106	-0.110	-1.136
	(0.00758)	(0.00825)	(0.0233)	(0.00922)	(0.0103)	(0.0308)
2 Years	-0.134	-0.127	-0.295	0.208	0.108	-0.561
	(0.00773)	(0.00829)	(0.0182)	(0.0137)	(0.0150)	(0.0302)
3 Years	-0.0454	-0.0250	-0.267	0.261	0.261	-0.363
	(0.0101)	(0.00859)	(0.0165)	(0.0192)	(0.0163)	(0.0299)
4 Years	-0.104	-0.0903	-0.296	0.236	0.230	-0.396
	(0.0100)	(0.00835)	(0.0165)	(0.0194)	(0.0167)	(0.0293)
5 Years	-0.325	-0.235	-0.457	0.0739	0.107	-0.482
	(0.00997)	(0.00819)	(0.0156)	(0.0215)	(0.0171)	(0.0292)
10 Years	-0.231	-0.207	-0.404	0.314	0.247	-0.379
	(0.00995)	(0.00838)	(0.0161)	(0.0218)	(0.0182)	(0.0310)
Observations	60,165	80,298	22,477	62,022	82,564	23,266
R-squared	0.067	0.033	0.044	0.012	0.014	0.081
Number of Individuals	18,567	20,952	5,941	18,593	20,967	5,958

Note: Robust Standard Errors in Parentheses
Dependent Variable in Columns 1-3 is the natural log of real PCE, in 4-6 it is the natural log of real HH assets
Dummy Variables Used to Estimate Differences from Each Year to Baseline
Individual Fixed-Effect Used

Table 3: Evolution of Real PCE and Real Assets for Males and Females by Damage Zone

	[1]	[2]	[3]	[4]	[5]	[6]
		lnPCE			ln(Real HH Assets)	
VARIABLES	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage
Constant (Baseline)	12.92	12.86	13.04	9.627	9.615	10.47
	(0.00569)	(0.00606)	(0.0123)	(0.00988)	(0.0109)	(0.0202)
1 Year	-0.335	-0.253	-0.361	0.117	-0.101	-1.046
	(0.0104)	(0.0114)	(0.0329)	(0.0129)	(0.0141)	(0.0421)
1 Year * Male	0.00375	0.00497	0.0524	-0.0233	-0.0198	-0.182
	(0.0152)	(0.0165)	(0.0467)	(0.0184)	(0.0206)	(0.0616)
2 Years	-0.142	-0.131	-0.338	0.227	0.126	-0.553
	(0.0104)	(0.0113)	(0.0254)	(0.0188)	(0.0204)	(0.0409)
2 Years * Male	0.0168	0.00667	0.0823	-0.0407	-0.0391	-0.0117
	(0.0156)	(0.0166)	(0.0363)	(0.0275)	(0.0302)	(0.0605)
3 Years	-0.0570	-0.0369	-0.311	0.296	0.286	-0.343
	(0.0135)	(0.0116)	(0.0230)	(0.0251)	(0.0218)	(0.0404)
3 Years * Male	0.0253	0.0254	0.0839	-0.0791	-0.0529	-0.0390
	(0.0205)	(0.0173)	(0.0330)	(0.0391)	(0.0327)	(0.0600)
4 Years	-0.116	-0.0960	-0.358	0.273	0.248	-0.407
	(0.0135)	(0.0113)	(0.0232)	(0.0260)	(0.0225)	(0.0399)
4 Years * Male	0.0273	0.0118	0.123	-0.0812	-0.0377	0.0269
	(0.0202)	(0.0168)	(0.0330)	(0.0390)	(0.0336)	(0.0588)
5 Years	-0.355	-0.252	-0.515	0.119	0.129	-0.447
	(0.0135)	(0.0111)	(0.0219)	(0.0287)	(0.0232)	(0.0397)
5 Years * Male	0.0654	0.0359	0.115	-0.101	-0.0478	-0.0710
	(0.0200)	(0.0164)	(0.0312)	(0.0433)	(0.0344)	(0.0585)
10 Years	-0.253	-0.225	-0.457	0.397	0.303	-0.313
	(0.0134)	(0.0114)	(0.0225)	(0.0292)	(0.0247)	(0.0420)
10 Years * Male	0.0476	0.0386	0.104	-0.178	-0.117	-0.135
	(0.0200)	(0.0168)	(0.0321)	(0.0438)	(0.0365)	(0.0622)
Observations	59,203	78,718	22,013	61,060	80,984	22,802
R-squared	0.067	0.033	0.045	0.013	0.015	0.082
Number of Individuals	17,605	19,372	5,477	17,631	19,387	5,494

Note: Robust Standard Errors in Parentheses

Dependent Variable in Columns 1-3 is the natural log of real PCE, in 4-6 it is the natural log of real HH assets

Dummy Variables Used to Estimate Differences from Each Year to Baseline

Individual Fixed-Effect Used

Table 4: Heterogeneity in the Evolution of Real PCE and Real Assets by Age and Education

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
		lnPCE						ln(Real HH Assets)					
		Females			Males			Females			Males		
	VARIABLES	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage
	Constant (Baseline)	12.92	12.87	13.06	12.92	12.88	13.02	9.640	9.645	10.49	9.665	9.631	10.53
		(0.00770)	(0.00835)	(0.0176)	(0.00820)	(0.00875)	(0.0168)	(0.0146)	(0.0168)	(0.0348)	(0.0154)	(0.0176)	(0.0340)
	1 Year	-0.359	-0.258	-0.480	-0.350	-0.272	-0.376	0.144	-0.109	-1.082	0.105	-0.109	-1.612
		(0.0231)	(0.0229)	(0.0722)	(0.0260)	(0.0255)	(0.0781)	(0.0309)	(0.0335)	(0.110)	(0.0328)	(0.0376)	(0.123)
	2 Years	-0.143	-0.111	-0.403	-0.117	-0.123	-0.206	0.261	0.187	-0.367	0.138	0.194	-0.612
		(0.0230)	(0.0228)	(0.0568)	(0.0277)	(0.0263)	(0.0598)	(0.0436)	(0.0453)	(0.107)	(0.0495)	(0.0518)	(0.121)
	3 Years	-0.0853	0.0205	-0.367	-0.00628	0.0506	-0.188	0.294	0.381	-0.117	0.163	0.310	-0.403
		(0.0298)	(0.0234)	(0.0511)	(0.0379)	(0.0281)	(0.0588)	(0.0587)	(0.0491)	(0.103)	(0.0751)	(0.0578)	(0.116)
	4 Years	-0.0819	-0.0417	-0.379	-0.0202	-0.00562	-0.149	0.320	0.362	-0.0870	0.0967	0.307	-0.291
		(0.0297)	(0.0229)	(0.0499)	(0.0369)	(0.0268)	(0.0559)	(0.0582)	(0.0498)	(0.101)	(0.0718)	(0.0583)	(0.109)
	5 Years	-0.351	-0.226	-0.511	-0.235	-0.144	-0.342	0.244	0.264	-0.138	-0.000816	0.136	-0.465
		(0.0299)	(0.0221)	(0.0479)	(0.0350)	(0.0262)	(0.0511)	(0.0632)	(0.0505)	(0.0989)	(0.0783)	(0.0600)	(0.116)
	10 Years	-0.306	-0.220	-0.538	-0.196	-0.187	-0.285	0.537	0.446	-0.0450	0.205	0.255	-0.580
		(0.0294)	(0.0224)	(0.0499)	(0.0347)	(0.0266)	(0.0531)	(0.0669)	(0.0542)	(0.104)	(0.0796)	(0.0629)	(0.116)
Age	1 Year * Age 30-45	0.0193	-0.0131	0.110	-0.00396	-0.0318	0.116	-0.0419	0.0102	0.0269	-0.0351	0.00914	0.132
		(0.0240)	(0.0263)	(0.0773)	(0.0256)	(0.0277)	(0.0767)	(0.0310)	(0.0359)	(0.105)	(0.0316)	(0.0376)	(0.109)
	1 Year * Age 45+	0.0256	0.0339	0.140	0.0199	-0.0275	0.105	0.0471	0.0349	0.146	-0.0298	0.0151	0.299
		(0.0320)	(0.0334)	(0.103)	(0.0322)	(0.0328)	(0.101)	(0.0408)	(0.0439)	(0.150)	(0.0359)	(0.0438)	(0.140)
	2 Years * Age30-45	-0.0264	-0.0566	0.0615	-0.0960	-0.0683	-0.0370	0.0218	0.0959	0.0823	0.0848	0.0782	0.0843
		(0.0236)	(0.0263)	(0.0586)	(0.0269)	(0.0284)	(0.0586)	(0.0450)	(0.0510)	(0.105)	(0.0508)	(0.0555)	(0.111)
	2 Years * Age 45+	0.0101	0.0149	0.0739	-0.000329	-0.0434	-0.0645	0.111	0.105	-0.0180	0.173	0.0257	0.0808
		(0.0324)	(0.0335)	(0.0778)	(0.0333)	(0.0343)	(0.0742)	(0.0591)	(0.0616)	(0.136)	(0.0557)	(0.0630)	(0.134)
	3 Years * Age 30-45	0.00101	-0.0730	0.0102	-0.130	-0.129	-0.0556	0.0593	0.0822	-0.0189	0.161	0.162	0.223
		(0.0318)	(0.0270)	(0.0511)	(0.0374)	(0.0300)	(0.0546)	(0.0589)	(0.0536)	(0.102)	(0.0730)	(0.0599)	(0.110)
	3 Years * Age 45+	0.0523	-0.0255	0.0808	-0.0318	-0.107	-0.0966	0.138	-0.0219	-0.0219	0.212	0.0512	0.0744
		(0.0423)	(0.0354)	(0.0750)	(0.0442)	(0.0367)	(0.0699)	(0.0756)	(0.0640)	(0.134)	(0.0826)	(0.0677)	(0.135)
	4 Years * Age 30-45	-0.0113	-0.0545	0.117	-0.159	-0.139	-0.0492	0.134	0.153	0.0929	0.336	0.304	0.214
		(0.0317)	(0.0267)	(0.0539)	(0.0356)	(0.0289)	(0.0543)	(0.0593)	(0.0545)	(0.101)	(0.0695)	(0.0604)	(0.105)
	4 Years & Age 45+	-0.0678	-0.0109	0.0634	-0.0657	-0.122	-0.0825	0.0988	0.0184	-0.0969	0.332	0.0362	0.0180
		(0.0420)	(0.0339)	(0.0721)	(0.0455)	(0.0347)	(0.0669)	(0.0751)	(0.0653)	(0.132)	(0.0816)	(0.0682)	(0.128)
	5 Years * Age 30-45	0.0116	-0.0235	0.0557	-0.194	-0.163	-0.0407	0.121	0.183	0.0218	0.416	0.405	0.261
		(0.0318)	(0.0256)	(0.0497)	(0.0345)	(0.0280)	(0.0503)	(0.0649)	(0.0559)	(0.0978)	(0.0748)	(0.0608)	(0.105)
	5 Years * Age 45+	-0.000397	0.0396	0.0780	-0.109	-0.0971	-0.0152	0.142	-0.0560	-0.0828	0.346	0.115	0.132
		(0.0423)	(0.0339)	(0.0683)	(0.0437)	(0.0337)	(0.0630)	(0.0815)	(0.0685)	(0.124)	(0.0897)	(0.0710)	(0.128)
	10 Years * Age 30-45	0.127	0.0730	0.209	-0.142	-0.0420	-0.0873	0.0678	0.162	0.0155	0.418	0.485	0.385
		(0.0312)	(0.0262)	(0.0506)	(0.0342)	(0.0284)	(0.0509)	(0.0657)	(0.0592)	(0.105)	(0.0754)	(0.0635)	(0.110)
	10 Years * Age 45+	0.0615	0.0655	0.205	-0.0273	-0.0301	0.0228	0.0263	-0.0854	-0.0985	0.271	0.127	0.332
		(0.0432)	(0.0349)	(0.0710)	(0.0444)	(0.0358)	(0.0657)	(0.0904)	(0.0719)	(0.144)	(0.0898)	(0.0752)	(0.131)
Educ.	1 Year * 7-12 Yrs Ed	0.0254	0.0329	0.128	0.0323	0.0863	-0.0164	-0.0260	0.0402	0.0618	0.0123	0.00591	0.384
		(0.0238)	(0.0249)	(0.0749)	(0.0249)	(0.0257)	(0.0750)	(0.0299)	(0.0343)	(0.109)	(0.0299)	(0.0352)	(0.116)
	1 Year * 13+ Yrs Ed	0.0365	-0.0550	0.00427	0.0295	0.0417	0.164	-0.154	-0.113	-0.0215	0.0703	-0.222	0.443
		(0.0554)	(0.0622)	(0.126)	(0.0611)	(0.0620)	(0.150)	(0.0661)	(0.0681)	(0.163)	(0.0643)	(0.0690)	(0.153)
	2 Years * 7-12 Yrs Ed	0.0108	0.0128	0.0990	0.0447	0.0744	0.0240	-0.116	-0.140	-0.217	-0.0684	-0.207	0.0518
		(0.0235)	(0.0250)	(0.0600)	(0.0258)	(0.0264)	(0.0587)	(0.0436)	(0.0486)	(0.106)	(0.0460)	(0.0510)	(0.114)
	2 Years * 13+ Yrs Ed	0.0565	-0.103	-0.0321	0.0510	0.0574	-0.139	-0.145	-0.475	-0.437	0.0121	-0.407	-0.351
		(0.0527)	(0.0595)	(0.0854)	(0.0619)	(0.0649)	(0.0936)	(0.0892)	(0.0998)	(0.166)	(0.0848)	(0.105)	(0.150)
	3 Years * 7-12 Yrs Ed	0.0557	-0.0478	0.0974	0.0670	0.0252	0.0403	-0.0636	-0.165	-0.242	-0.0624	-0.200	-0.0816
		(0.0314)	(0.0256)	(0.0532)	(0.0352)	(0.0280)	(0.0554)	(0.0580)	(0.0515)	(0.102)	(0.0667)	(0.0548)	(0.108)
	3 Years * 13+ Yrs Ed	-0.0218	-0.104	-0.00396	0.0362	0.0748	-0.0476	-0.142	-0.341	-0.412	0.0282	-0.355	-0.369
		(0.0639)	(0.0666)	(0.0838)	(0.0734)	(0.0706)	(0.0893)	(0.111)	(0.101)	(0.166)	(0.122)	(0.107)	(0.175)
	4 Years * 7-12 Yrs Ed	-0.0269	-0.0507	0.00149	0.00841	0.0109	-0.0433	-0.167	-0.258	-0.412	-0.157	-0.312	-0.176
		(0.0309)	(0.0253)	(0.0532)	(0.0348)	(0.0271)	(0.0548)	(0.0582)	(0.0527)	(0.102)	(0.0647)	(0.0553)	(0.103)
	4 Years * 13+ Yrs Ed	-0.0311	-0.247	-0.181	0.00495	-0.00269	-0.279	-0.167	-0.381	-0.662	-0.121	-0.407	-0.474
		(0.0670)	(0.0630)	(0.0842)	(0.0735)	(0.0638)	(0.0832)	(0.111)	(0.104)	(0.162)	(0.117)	(0.109)	(0.156)
	5 Years * 7-12 Yrs Ed	-0.0149	-0.0370	-0.0312	0.0541	0.0190	-0.00386	-0.247	-0.269	-0.372	-0.270	-0.327	-0.198
		(0.0310)	(0.0244)	(0.0507)	(0.0334)	(0.0264)	(0.0497)	(0.0634)	(0.0543)	(0.0979)	(0.0713)	(0.0570)	(0.106)
	5 Years * 13+ Yrs Ed	-0.106	-0.242	-0.153	-0.0737	-0.113	-0.284	-0.282	-0.333	-0.460	-0.122	-0.298	-0.308
		(0.0623)	(0.0622)	(0.0735)	(0.0663)	(0.0583)	(0.0762)	(0.115)	(0.107)	(0.157)	(0.125)	(0.108)	(0.151)
	10 Years * 7-12 Yrs Ed	-0.0108	-0.0798	-0.0698	0.0305	0.00185	-0.0768	-0.206	-0.181	-0.289	-0.209	-0.250	-0.0444
		(0.0306)	(0.0249)	(0.0519)	(0.0337)	(0.0271)	(0.0518)	(0.0661)	(0.0571)	(0.105)	(0.0730)	(0.0605)	(0.110)
	10 Years * 13+ Yrs Ed	-0.149	-0.353	-0.152	-0.0891	-0.202	-0.261	-0.159	-0.284	-0.332	0.0683	-0.373	0.0156
		(0.0672)	(0.0611)	(0.0750)	(0.0703)	(0.0588)	(0.0810)	(0.118)	(0.113)	(0.168)	(0.123)	(0.115)	(0.156)
	Observations	28,227	36,473	10,072	24,125	31,990	9,378	28,232	36,500	10,080	24,149	32,042	9,385
	R-squared	0.079	0.045	0.068	0.074	0.042	0.052	0.023	0.030	0.080	0.020	0.027	0.113
	Number of Individuals	7,501	7,553	2,149	6,907	7,260	2,193	7,501	7,553	2,149	6,909	7,261	2,193

Note: Robust Standard Errors in Parentheses
Dependent Variable in Columns 1-6 is the natural log of real PCE, in 7-12 it is the natural log of real HH assets
Dummy Variables Used to Estimate Differences from Each Year to Baseline
"Ed." Referes to indicators for different levels of years of educatioin
0-6 Years of Education and 15-30 Years Old Categories are the "Excluded" categories for the indicator variables
Individual Fixed-Effect Used

Table 5: Urban and Rural Differences in the Trajectory of Real PCE and Real Assets by Damage Zone and Gender

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	lnPCE						ln(Real HH Assets)					
	Females			Males			Females			Males		
VARIABLES	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage
Constant (Baseline)	12.92	12.86	13.05	12.92	12.88	13.01	9.642	9.641	10.49	9.668	9.626	10.52
	(0.00752)	(0.00813)	(0.0173)	(0.00802)	(0.00851)	(0.0166)	(0.0143)	(0.0164)	(0.0343)	(0.0151)	(0.0171)	(0.0336)
1 Year	-0.330	-0.249	-0.287	-0.316	-0.240	-0.149	0.101	-0.104	-1.026	0.0681	-0.133	-1.324
	(0.0116)	(0.0137)	(0.0427)	(0.0126)	(0.0143)	(0.0426)	(0.0153)	(0.0185)	(0.0684)	(0.0149)	(0.0195)	(0.0667)
1 Year * Urban	-0.0154	0.0255	-0.122	-0.0410	0.0119	-0.304	0.0369	0.0187	-0.00455	0.0824	0.0404	0.169
	(0.0268)	(0.0254)	(0.0680)	(0.0272)	(0.0267)	(0.0686)	(0.0339)	(0.0329)	(0.0941)	(0.0337)	(0.0353)	(0.0985)
2 Years	-0.127	-0.118	-0.184	-0.110	-0.104	-0.140	0.264	0.213	-0.262	0.166	0.142	-0.436
	(0.0117)	(0.0132)	(0.0355)	(0.0130)	(0.0143)	(0.0340)	(0.0224)	(0.0260)	(0.0670)	(0.0235)	(0.0279)	(0.0650)
2 Years * Urban	-0.0572	-0.0227	-0.304	-0.0509	-0.0297	-0.206	-0.146	-0.219	-0.486	0.0329	-0.164	-0.337
	(0.0264)	(0.0262)	(0.0516)	(0.0296)	(0.0285)	(0.0537)	(0.0519)	(0.0510)	(0.0927)	(0.0551)	(0.0559)	(0.0998)
3 Years	-0.0201	-0.00234	-0.251	0.00641	0.0308	-0.140	0.367	0.390	-0.143	0.302	0.315	-0.310
	(0.0163)	(0.0138)	(0.0326)	(0.0188)	(0.0151)	(0.0317)	(0.0305)	(0.0275)	(0.0644)	(0.0350)	(0.0300)	(0.0611)
3 Years * Urban	-0.0991	-0.105	-0.0868	-0.0783	-0.115	-0.129	-0.206	-0.250	-0.307	-0.215	-0.189	-0.212
	(0.0315)	(0.0269)	(0.0466)	(0.0364)	(0.0302)	(0.0494)	(0.0617)	(0.0539)	(0.0926)	(0.0748)	(0.0597)	(0.101)
4 Years	-0.0558	-0.0515	-0.228	-0.0309	-0.0432	-0.127	0.342	0.376	-0.0483	0.240	0.326	-0.207
	(0.0159)	(0.0133)	(0.0315)	(0.0177)	(0.0145)	(0.0305)	(0.0311)	(0.0285)	(0.0626)	(0.0343)	(0.0305)	(0.0598)
4 Years * Urban	-0.205	-0.159	-0.264	-0.202	-0.115	-0.257	-0.176	-0.331	-0.652	-0.178	-0.321	-0.381
	(0.0326)	(0.0264)	(0.0475)	(0.0368)	(0.0290)	(0.0490)	(0.0638)	(0.0552)	(0.0921)	(0.0733)	(0.0611)	(0.0960)
5 Years	-0.316	-0.230	-0.434	-0.256	-0.197	-0.309	0.235	0.280	-0.206	0.0927	0.185	-0.419
	(0.0160)	(0.0126)	(0.0297)	(0.0175)	(0.0139)	(0.0290)	(0.0335)	(0.0292)	(0.0623)	(0.0381)	(0.0318)	(0.0606)
5 Years * Urban	-0.168	-0.0903	-0.145	-0.163	-0.0642	-0.180	-0.220	-0.360	-0.357	-0.149	-0.265	-0.158
	(0.0320)	(0.0268)	(0.0445)	(0.0355)	(0.0289)	(0.0455)	(0.0699)	(0.0566)	(0.0905)	(0.0808)	(0.0612)	(0.0957)
10 Years	-0.243	-0.179	-0.403	-0.214	-0.171	-0.323	0.549	0.559	-0.0181	0.380	0.428	-0.359
	(0.0157)	(0.0132)	(0.0307)	(0.0174)	(0.0144)	(0.0312)	(0.0339)	(0.0305)	(0.0627)	(0.0378)	(0.0329)	(0.0653)
10 Years * Urban	-0.117	-0.233	-0.186	-0.111	-0.210	-0.152	-0.307	-0.517	-0.462	-0.251	-0.448	-0.0595
	(0.0323)	(0.0264)	(0.0460)	(0.0357)	(0.0285)	(0.0463)	(0.0756)	(0.0601)	(0.0972)	(0.0829)	(0.0653)	(0.101)
Observations	27,899	35,579	9,715	23,821	31,277	9,096	27,904	35,603	9,723	23,844	31,330	9,103
R-squared	0.080	0.046	0.067	0.072	0.041	0.050	0.024	0.034	0.089	0.014	0.024	0.110
Number of Individuals	7,427	7,377	2,072	6,823	7,106	2,128	7,427	7,377	2,072	6,825	7,107	2,128

Note: Robust Standard Errors in Parentheses
Dependent Variable in Columns 1-6 is the natural log of real PCE, in 7-12 it is the natural log of real HH assets
Dummy Variables Used to Estimate Differences from Each Year to Baseline
The interaction term X Years * Urban shows the difference in outcome between rural (not explicitly shown) and urban areas
Individual Fixed-Effect Used

Table 6: Differences in Real PCE and Real Assets Over Time by Refugee Camp Status

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	lnPCE				ln(Real HH Assets)			
	Females		Males		Females		Males	
VARIABLES	Moderate Damage	High Damage	Moderate Damage	High Damage	Moderate Damage	High Damage	Moderate Damage	High Damage
Constant (Baseline)	12.87	13.06	12.88	13.02	9.667	10.55	9.650	10.54
	(0.00825)	(0.0175)	(0.00866)	(0.0170)	(0.0145)	(0.0274)	(0.0157)	(0.0295)
Year 1	-0.248	-0.306	-0.243	-0.262	-0.0354	-0.690	-0.0536	-0.723
	(0.0135)	(0.0540)	(0.0144)	(0.0615)	(0.0165)	(0.0606)	(0.0174)	(0.0702)
Year 1 * Camps	0.00659	-0.0850	0.0229	-0.0533	-0.272	-0.654	-0.289	-0.834
	(0.0262)	(0.0683)	(0.0272)	(0.0739)	(0.0311)	(0.0833)	(0.0351)	(0.0918)
Year 2	-0.134	-0.413	-0.127	-0.389	0.202	-0.524	0.114	-0.445
	(0.0137)	(0.0419)	(0.0149)	(0.0465)	(0.0243)	(0.0624)	(0.0269)	(0.0754)
Year 2 * Camps	0.0224	0.144	0.0459	0.241	-0.295	-0.0628	-0.174	-0.244
	(0.0251)	(0.0530)	(0.0270)	(0.0563)	(0.0454)	(0.0832)	(0.0494)	(0.0941)
Year 3	-0.0415	-0.341	-0.0114	-0.280	0.324	-0.351	0.236	-0.306
	(0.0142)	(0.0388)	(0.0157)	(0.0410)	(0.0264)	(0.0672)	(0.0300)	(0.0772)
Year 3 * Camps	0.0253	0.0609	0.0435	0.110	-0.139	-0.0164	-0.0560	-0.179
	(0.0259)	(0.0481)	(0.0284)	(0.0508)	(0.0485)	(0.0842)	(0.0536)	(0.0950)
Year 4	-0.0935	-0.427	-0.0674	-0.310	0.303	-0.501	0.222	-0.340
	(0.0136)	(0.0388)	(0.0153)	(0.0417)	(0.0276)	(0.0648)	(0.0307)	(0.0786)
Year 4 * Camps	-0.0136	0.126	-0.0149	0.113	-0.175	0.134	-0.0646	-0.0775
	(0.0258)	(0.0487)	(0.0269)	(0.0509)	(0.0496)	(0.0825)	(0.0546)	(0.0938)
Year 5	-0.254	-0.575	-0.216	-0.471	0.225	-0.445	0.119	-0.459
	(0.0134)	(0.0350)	(0.0146)	(0.0370)	(0.0281)	(0.0626)	(0.0314)	(0.0768)
Year 5 * Camps	-0.00961	0.110	0.00152	0.124	-0.263	0.00447	-0.132	-0.0798
	(0.0250)	(0.0449)	(0.0270)	(0.0465)	(0.0513)	(0.0806)	(0.0554)	(0.0926)
Year 10	-0.239	-0.498	-0.220	-0.393	0.485	-0.289	0.347	-0.251
	(0.0135)	(0.0353)	(0.0149)	(0.0373)	(0.0296)	(0.0667)	(0.0329)	(0.0811)
Year 10 * Camps	-0.0245	0.00767	-0.0199	0.00913	-0.421	-0.00183	-0.316	-0.273
	(0.0262)	(0.0462)	(0.0276)	(0.0477)	(0.0547)	(0.0861)	(0.0593)	(0.0983)
Observations	36,246	10,025	31,682	9,291	37,353	10,458	32,583	9,574
R-squared	0.040	0.064	0.037	0.047	0.027	0.094	0.018	0.118
Number of Individuals	7,417	2,119	7,071	2,139	7,418	2,124	7,079	2,147

Note: Robust Standard Errors in Parentheses

Dependent Variable in Columns 1-6 is the natural log of real PCE, in 7-12 it is the natural log of real HH

Dummy Variables Used to Estimate Differences from Each Year to Baseline

"Camps" represents an indicator variable that represents if an individual moved into a refugee camp at any point

The interaction term X Years * Camps shows the difference in outcome between people who did not move to camps (not explicitly shown) and those who did

Individual Fixed-Effect Used

Table 7: Inequality Across and Within Damage Zones Over Time

	[1]	[2]	[3]	[4]	[5]	[6]
	Inequality calculated by Damage Zone within each				Inequality metrics overall	
VARIABLES	CV trimmed real lnpce	CV real lnpce	CV trimmed real assets	CV real assets	Overall CV lnpce	Overall CV Assets
Constant (Baseline)	0.0433	0.0447	1.201	2.178	0.0450	2.215
Dmg Med	0.000783	0.00104	-0.0177	0.0838		
Dmg High	-0.00160	-0.00197	-0.299	-0.389		
Year 1	0.0103	0.0105	-0.0651	0.177	0.0170	0.504
Year 1 * Dmg Med	0.00480	0.00535	0.0530	-0.350		
Yeare 1 * Dmg High	0.0259	0.0319	8.160	4.424		
Year 2	0.00882	0.00875	-0.0951	-0.0362	0.0118	-0.135
Year 2 * Dmg Med	0.00271	0.00324	-0.00902	-0.108		
Year 2 * Dmg High	0.0144	0.0144	0.105	-0.0632		
Year 3	0.0101	0.0102	-0.201	-0.379	0.0115	-0.468
Year 3 * Dmg Med	0.000824	0.000519	0.0641	-0.143		
Year 3 * Dmg High	0.00512	0.00590	0.143	0.204		
Year 4	0.00889	0.00905	-0.220	-0.441	0.00910	-0.509
Year 4 * Dmg Med	-0.000478	-0.000792	0.0973	-0.0702		
Year 4 * Dmg High	0.00323	0.00304	0.145	0.0852		
Year 5	0.00686	0.00599	-0.178	-0.574	0.00726	-0.520
Year 5 * Dmg Med	0.000858	0.00126	0.109	0.0866		
Year 5 * Dmg High	0.00223	0.00357	0.144	0.368		
Year 10	0.00501	0.00456	-0.206	-0.564	0.00519	-0.430
Year 10 * Dmg Med	0.000227	-0.000343	0.135	0.173		
Year 10 * Dmg High	0.00552	0.00538	0.301	0.594		
Observations	154,542	162,943	161,258	170,091	163,334	170,537
R-squared	1.000	1.000	1.000	1.000	1.000	1.000

Note: Inequality Calculated at Damage Zone Level, so R^2=1, No Standard Errors Reported
Dummy Variables Used to Estimate Differences from Each Year to Baseline
"Dmg Med" and "Dmg High" Represent dummy variables that indicate damage exposure
The interaction term X Years * Dmg shows the difference in outcome between areas not directly affected (not explicitly shown) and damaged areas

Table 8: Heterogeneity in the Evolution of Real PCE and Real Assets by Pre-Tsunami PCE and Asset Percentiles

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	lnPCE						ln(Real HH Assets)					
	Females			Males			Females			Males		
VARIABLES	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage
Constant (Baseline)	12.92	12.87	13.05	12.92	12.88	13.02	9.671	9.683	10.59	9.696	9.673	10.57
	(0.00628)	(0.00685)	(0.0155)	(0.00672)	(0.00722)	(0.0148)	(0.0103)	(0.0115)	(0.0207)	(0.0112)	(0.0126)	(0.0222)
1 Year	-0.332	-0.272	-0.299	-0.324	-0.253	-0.204	0.0108	-0.217	-0.967	0.0236	-0.232	-1.179
	(0.0119)	(0.0139)	(0.0419)	(0.0126)	(0.0145)	(0.0433)	(0.0101)	(0.0137)	(0.0551)	(0.0111)	(0.0148)	(0.0598)
1 Year * 80th %ile	-0.441	-0.373	-0.423	-0.485	-0.415	-0.615	-0.169	-0.138	-0.449	-0.182	-0.142	-0.424
	(0.0294)	(0.0303)	(0.0778)	(0.0307)	(0.0316)	(0.0803)	(0.0224)	(0.0289)	(0.0830)	(0.0236)	(0.0298)	(0.0870)
1 Year * 20th %ile	0.403	0.431	0.615	0.423	0.422	0.480	0.547	0.668	1.346	0.467	0.653	1.442
	(0.0256)	(0.0274)	(0.101)	(0.0265)	(0.0295)	(0.0898)	(0.0442)	(0.0457)	(0.167)	(0.0448)	(0.0502)	(0.203)
2 Years	-0.150	-0.158	-0.259	-0.135	-0.129	-0.172	0.0412	-0.0235	-0.349	0.00775	-0.0772	-0.393
	(0.0121)	(0.0136)	(0.0330)	(0.0134)	(0.0147)	(0.0353)	(0.0196)	(0.0209)	(0.0520)	(0.0222)	(0.0233)	(0.0558)
2 Years * 80th %ile	-0.495	-0.412	-0.379	-0.503	-0.468	-0.406	-0.540	-0.728	-0.892	-0.438	-0.748	-0.953
	(0.0279)	(0.0295)	(0.0590)	(0.0316)	(0.0336)	(0.0586)	(0.0462)	(0.0489)	(0.0744)	(0.0473)	(0.0560)	(0.0803)
2 Years * 20th %ile	0.469	0.497	0.373	0.485	0.478	0.274	1.181	1.372	1.782	1.063	1.387	1.937
	(0.0247)	(0.0270)	(0.0838)	(0.0276)	(0.0290)	(0.0804)	(0.0525)	(0.0575)	(0.162)	(0.0565)	(0.0620)	(0.190)
3 Years	-0.0432	-0.0421	-0.239	-0.0179	-0.00667	-0.170	0.127	0.145	-0.0129	0.0971	0.0690	-0.122
	(0.0171)	(0.0142)	(0.0298)	(0.0200)	(0.0154)	(0.0311)	(0.0278)	(0.0223)	(0.0489)	(0.0329)	(0.0260)	(0.0519)
3 Years * 80th %ile	-0.534	-0.497	-0.323	-0.576	-0.520	-0.320	-0.702	-0.948	-1.174	-0.780	-0.879	-1.172
	(0.0382)	(0.0313)	(0.0532)	(0.0422)	(0.0354)	(0.0580)	(0.0586)	(0.0515)	(0.0713)	(0.0776)	(0.0597)	(0.0785)
3 Years * 20th %ile	0.454	0.471	0.401	0.448	0.477	0.382	1.447	1.548	1.647	1.417	1.603	1.961
	(0.0349)	(0.0276)	(0.0622)	(0.0419)	(0.0313)	(0.0659)	(0.0720)	(0.0580)	(0.154)	(0.0839)	(0.0663)	(0.186)
4 Years	-0.124	-0.111	-0.243	-0.0794	-0.0982	-0.168	0.136	0.104	-0.107	0.0658	0.0394	-0.128
	(0.0164)	(0.0135)	(0.0291)	(0.0186)	(0.0146)	(0.0306)	(0.0291)	(0.0238)	(0.0470)	(0.0328)	(0.0264)	(0.0489)
4 Years * 80th %ile	-0.578	-0.559	-0.585	-0.673	-0.522	-0.547	-0.815	-1.069	-1.184	-0.832	-0.973	-1.131
	(0.0397)	(0.0285)	(0.0523)	(0.0417)	(0.0321)	(0.0551)	(0.0622)	(0.0555)	(0.0698)	(0.0750)	(0.0602)	(0.0718)
4 Years * 20th %ile	0.523	0.548	0.439	0.505	0.533	0.406	1.477	1.648	1.812	1.425	1.721	2.053
	(0.0329)	(0.0273)	(0.0653)	(0.0379)	(0.0306)	(0.0637)	(0.0705)	(0.0561)	(0.147)	(0.0784)	(0.0647)	(0.175)
5 Years	-0.362	-0.275	-0.411	-0.291	-0.228	-0.297	0.0309	0.00960	-0.133	-0.0616	-0.105	-0.250
	(0.0170)	(0.0129)	(0.0268)	(0.0194)	(0.0140)	(0.0280)	(0.0328)	(0.0245)	(0.0468)	(0.0363)	(0.0279)	(0.0494)
5 Years * 80th %ile	-0.626	-0.501	-0.521	-0.628	-0.535	-0.554	-0.892	-1.108	-1.145	-0.960	-0.934	-1.095
	(0.0386)	(0.0285)	(0.0476)	(0.0400)	(0.0310)	(0.0509)	(0.0683)	(0.0562)	(0.0688)	(0.0822)	(0.0617)	(0.0722)
5 Years * 20th %ile	0.505	0.548	0.467	0.468	0.537	0.370	1.524	1.639	1.711	1.522	1.723	2.075
	(0.0336)	(0.0265)	(0.0636)	(0.0356)	(0.0293)	(0.0588)	(0.0787)	(0.0585)	(0.140)	(0.0905)	(0.0649)	(0.180)
10 Years	-0.257	-0.261	-0.385	-0.222	-0.219	-0.293	0.271	0.214	0.0175	0.108	0.0817	-0.113
	(0.0163)	(0.0126)	(0.0269)	(0.0185)	(0.0137)	(0.0289)	(0.0317)	(0.0266)	(0.0503)	(0.0379)	(0.0288)	(0.0529)
10 Years * 80th %ile	-0.679	-0.631	-0.584	-0.675	-0.653	-0.602	-0.967	-1.226	-1.214	-0.989	-1.171	-1.266
	(0.0382)	(0.0270)	(0.0493)	(0.0396)	(0.0287)	(0.0522)	(0.0708)	(0.0567)	(0.0751)	(0.0797)	(0.0675)	(0.0815)
10 Years * 20th %ile	0.544	0.648	0.514	0.521	0.593	0.451	1.771	1.766	1.878	1.720	1.828	1.977
	(0.0306)	(0.0267)	(0.0655)	(0.0349)	(0.0305)	(0.0596)	(0.0791)	(0.0619)	(0.152)	(0.0863)	(0.0684)	(0.175)
Observations	25,123	32,244	8,688	21,662	28,526	8,108	26,825	34,703	9,769	23,026	30,639	8,924
R-squared	0.145	0.099	0.097	0.141	0.093	0.083	0.126	0.141	0.176	0.107	0.125	0.207
Number of Individuals	6,555	6,376	1,741	6,023	6,101	1,762	6,812	6,732	1,921	6,278	6,487	1,940

Note: Robust Standard Errors in Parentheses
Dependent Variable in Columns 1-6 is the natural log of real PCE, in 7-12 it is the natural log of real HH assets
Dummy Variables Used to Estimate Differences from Each Year to Baseline
"20th %ile" Represents a dummy variable that indicates if an individual was in the bottom 20% of PCE or Assets, respectively, before the tsunami
"80th %ile" Represents a dummy variable that indicates if an individual was in the top 20% of PCE or Assets, respectively, before the tsunami
The interaction term X Years * XX %ile shows the difference in outcome between people who were in the top and bottom of the distribution of Assets or PCE at baseline
Individual Fixed-Effect Used

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Appendix

Appendix Table 1 displays individual fixed-effect results for self-reported economic well-being, rather than PCE or assets. Appendix 2 shows differences in key outcomes at baseline between damage zones, controlling for demographic differences between damage zones. Appendix 3 repeats the primary specification of the paper, without accounting for price effects.

Appendix 1: Trends in Self-Reported Economic Wellbeing Over Time

	[1] Not Directly Affected	[2] Moderate Damage	[3] High Damage
Baseline	2.653	2.583	2.970
	(0.00740)	(0.00794)	(0.0160)
1 Year	2.603	2.493	2.562
	(0.00770)	(0.00804)	(0.0158)
2 Years	2.790	2.712	2.853
	(0.00727)	(0.00746)	(0.0148)
3 Years	2.801	2.778	2.918
	(0.0122)	(0.00928)	(0.0154)
4 Years	2.970	2.884	2.998
	(0.0109)	(0.00787)	(0.0134)
5 Years	3.027	2.957	3.030
	(0.0104)	(0.00857)	(0.0150)
10 Years	2.781	2.734	2.861
	(0.00906)	(0.00679)	(0.0122)
Observations	19,501	21,218	6,312

Note: Robust Standard Errors in Parentheses
Dummy Variables Used to Estimate Differences from Each Year to Baseline
Outcome is Self-Reported Economic Wellbeing, using a modified Cantril Ladder Question

Appendix 2: Differences in Key Outcomes between Damage Zones, Controlling for Demographics

	[1] Real lnPCE	[2] Real lnAssets
Moderately Damaged	-0.0708	-0.0416
	(0.0145)	(0.0783)
Heavily Damaged	0.0123	0.0885
	(0.0289)	(0.135)
Observations	20,862	20,882
R-squared	0.143	0.137

Note: Robust Standard Errors in Parentheses
"Dmg Med" and "Dmg High" Represent dummy variables that indicate damage exposure
Controlling for Gender, Education, Age, Household Structure
Kecamatan Level Fixed Effects Used

Appendix 3: Trajectory of Nominal Outcomes Over Time

	[1]	[2]	[3]	[4]	[5]	[6]
		lnPCE			ln(Real HH Assets)	
VARIABLES	Not Directly Affected	Moderate Damage	High Damage	Not Directly Affected	Moderate Damage	High Damage
Constant (Baseline)	12.65	12.61	12.79	9.342	9.358	10.21
	(0.00571)	(0.00606)	(0.0116)	(0.00968)	(0.0105)	(0.0196)
1 Year	-0.192	-0.0209	0.271	0.239	0.104	-0.514
	(0.00755)	(0.00822)	(0.0204)	(0.00868)	(0.00975)	(0.0280)
2 Years	0.0861	0.206	0.471	0.418	0.423	0.200
	(0.00770)	(0.00831)	(0.0168)	(0.0131)	(0.0144)	(0.0276)
3 Years	0.386	0.428	0.518	0.669	0.692	0.440
	(0.00981)	(0.00854)	(0.0157)	(0.0187)	(0.0158)	(0.0289)
4 Years	0.482	0.529	0.653	0.807	0.828	0.553
	(0.00983)	(0.00828)	(0.0151)	(0.0192)	(0.0163)	(0.0284)
5 Years	0.533	0.587	0.667	0.935	0.908	0.646
	(0.00938)	(0.00810)	(0.0143)	(0.0204)	(0.0167)	(0.0285)
10 Years	0.911	0.897	0.893	1.445	1.330	0.941
	(0.00970)	(0.00817)	(0.0149)	(0.0214)	(0.0177)	(0.0303)
Observations	62,014	81,353	23,459	64,975	84,531	24,454
R-squared	0.283	0.269	0.183	0.151	0.150	0.148
Number of Individuals	18,701	21,162	6,028	18,724	21,175	6,036

Note: Robust Standard Errors in Parentheses
Dependent Variable in Columns 1-3 is the natural log of nominal PCE, in 4-6 it is the natural log of nominal HH assets
Dummy Variables Used to Estimate Differences from Each Year to Baseline
Individual Fixed-Effect Used