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CESIFO WORKING PAPER NO. 6136

CATEGORY 9: RESOURCE AND ENVIRONMENT ECONOMICS

OCTOBER 2016

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ISSN 2364-1428

CESifo

Center for Economic Studies & Ifo Institute

CESifo *Working Paper No. 6136*

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Abstract

We estimate the causal effect of the Indian Ocean tsunami in Sri Lanka on household income and consumption eight years after the event, using a quasi-experimental method. A strong association between area-wide tsunami disaster shock and increases in household income and consumption in the long-term emerged from our empirical investigation. Deviating from the common observation on short-term impacts, these results are suggestive of an optimistic potential for some long-lasting potentially successful recovery scenarios. Still, Sri Lanka received a very large amount of external transfers post-tsunami, much larger than is typical for disaster events and one which may not be replicable in other cases. Our findings suggest a more nuanced picture with respect to household consumption impacts. We observe a reduction of food consumption and only find an increase in non-food consumption. The increase in non-food consumption is much smaller than the observed increase in income. We also find that households in high-income regions experienced much better recovery from the disaster.

JEL-Codes: Q540, R110.

Keywords: Sri Lanka, tsunami, disaster, household survey, long-run impact.

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September 2016

1. Introduction

The 2004 Indian Ocean earthquake elevated the ocean floor by at least three meters generating a very powerful tsunami that killed 226,000 and displaced more than 2 million people in about a dozen countries. A large number of casualties and property damage associated with high-intensity disasters like tsunamis obviously have short term impacts by reducing economic activity, but relatively less is known about the long-term economic losses.[1] Here, we are interested in households' vulnerability to the long-term impacts of the disaster; specifically, we aim to identify the impact of the tsunami on Sri Lankan households. In this case, the event was completely unexpected and thus undoubtedly exogenous, but its impact is not. Households' socio-economic characteristics, their exposure and vulnerability to the hazard itself, their resilience and access to tools and mechanisms to manage the disaster's aftermath, their preferences, their decisions when the circumstances around them change, and their choices during the post-event reconstruction all eventually determined the disaster's long-term consequences (Hallegatte *et al,* 2014; Hallegatte and Przyluski, 2010; McCarthy and Smith, 2009; Mechler, Bayer, & Peppiatt, 2006; World Bank, 2013).

Sri Lanka, an island country in the Indian Ocean, is densely populated, with a 2015 population of 20.7 million (Central Bank, 2015). The population is 74.9% Sinhalese, 11.2% Sri Lankan Tamil, 4.1% Indian Tamil, and 9.3% Sri Lankan Moor. 20.5%, 26.3% and 45% of population work in the agriculture, industry and service sectors, respectively (Department of Census and Statistics, 2012). Administratively, Sri Lanka is divided into 9 Provinces, and these are divided further into 25 Districts. Each District is divided into Divisional Secretariats (DS). Each DS consists of several Grama Niladhari (GN) Divisions, the lowest administrative unit. Currently, there are 324 DS Divisions and 14,009 GN Divisions in the country (Department of Census and Statistics, 2015). In the World Bank's classification, Sri Lanka is a lower-middle income country, though social indicators suggest a higher standard of living when compared to other countries in South Asia. From the early 1980s, the country was impacted by an armed uprising; seven districts out of 25 were intensely affected by the

[1] Economic losses – sometime referred to as induced or indirect losses – are considered in terms of changes to flows of goods, services and business or even government revenues. These can emerge in various spatial scales, in different economic sectors, and can change rapidly or evolve slowly over longer periods of time (Rose, 2009; Hallegate & Przyluski, 2010; Cochrane, 2004).

conflict with the Liberation Tigers of Tamil Eelam (LTTE). The armed conflict ended in 2010. Prior to the 2004 tsunami, approximately 25 percent of the population lived in the coastal region, while 70 percent of tourist hotels and 62 percent of industrial units and almost all fisheries were also located there.

The tsunami reached 13 Districts out of 14 coastal districts, the death toll reached almost 35,500, and the disaster affected more than one million people. Infrastructure was severely damaged and the overall economic losses totalled USD 1.5 billion, approximately 5% of the country's GDP (Department of Census and Statistics, 2005) – a figure proportionally similar to the damage experienced by Japan in the 2011 earthquake/tsunami disaster. Tourism and fisheries were the two sectors most seriously affected. 150,000 people lost their main income source, 50% of them in the fisheries sector. Before 2004, tourism was one of the top income earners in Sri Lanka with the gross earnings amounting to USD 416 million during 2004 from peak tourist arrivals of 566,200.

A decade after this catastrophic disaster, this paper evaluates the long-term household-level consequences of this event in Sri Lanka. The average effect of the tsunami on household income and consumption residign in the seven affected districts is examined in quasi-experimental (diff-in-diff) setting using cross sectional household data. Since the intensity of damages—death, displacement and property damag caused by tsunami—vary across districts, the analysis also sheds light on the spatial dynamics of the disaster recovery.

2. Related Literature on Disaster Losses

The literature on the losses associated with disasters examines consequences at both the micro- and macro-level. At the macro level, the available empirical evidence does not reach any consensus view, but much of the variance in results is a function of the different foci in each paper—the spatial scale, type of disaster, time horizon, etc. Two recent papers provide regression meta-analysis of this literature (Klomp and Valckx, 2014; Lazzaroni and van Bergeijk, 2014). This literature, however, provides few details about the causal channels that lead from the trigger event itself to the macroeconomic aggregate impacts that are identified (be they on aggregate employment or unemployment, production, or fiscal and trade deficits). The micro-econometric literature is better placed to provide some impetus for the important endeavour of unveiling these causal chains.

In the short term, households manage the financial risk they are exposed to because of natural hazards through several risk transfer and risk management tools. Explicit insurance contracts and credit are the primary market-based arrangements available to manage financial risks, but implicit insurance arrangements (from kin, from governments, or from the international community) also play a role in transferring risk away from affected households.[2] Similarly for firms, the availability of resources for post-disaster appears to play a central role in post-disaster recovery.[3]

The literature, however, suggests that low-income households are credit constrained and their ability to self-insure is limited. This results in variation in expenditures associated with realized risks (Mogues, 2011; Baez and Mason, 2008; Carter et al., 2007; Baez, 2006; Jansen and Carter, 2013). Because of inadequate risk transfer, poor households use costly ways to confront risk, ways that may have long-lasting adverse consequences. These consequences can be especially severe for the poorest households (Dercon and Christiaensen, 2011; Dercon et al., 2007).

Households accumulate saving to cushion the welfare loss. Evidence suggests that household saving is higher in countries with greater risk exposure and frequency of intense disasters (Aizenman and Noy, 2015; Skidmore, 2001). When productive assets are lost due to disaster, households may need to reduce consumption to protect their remaining assets (Barrett *et al*., 2007; Kazianga and Udry, 2006; Little et al., 2006). Either way, they can fall into “poverty traps” from which recovery is difficult without external asssistance. Carter and Barrett (2006), for example, provide evidence for such ‘asset poverty traps’ among pastoralists in northern Kenya.

Reductions in household consumption can have significant adverse consequences to well-being, including even reduced height and body mass index for children experiencing these events (Alderman, Haddinot and Kinsey, 2006; Haddinot, 2006). In the cross-country analysis, Cuaresma (2009) revealed a strong negative correlation between disasters and secondary school enrolment. Further, Bhalotra, Sanhueza and Wu (2011) revealed evidence

[2] Sawada and Shimizutani (2007), for example, observe that the households with collateral and free from binding borrowing constraints were better able to cope with income loss following the 1995 Kobe earthquake. With limited access to explicit risk transfer financial instruments, the poor respond to shocks by pooling risk through social mechanisms such as credit cooperatives and mutual assistance pools (Baez, 2006; Little *et al*, 2006; World Bank, 2013).

[3] Following the tsunami, Sri Lankan firms with access to loans or grants performed better (De Mel et al., 2011).

from Chile and Cruso and Miller (2015) from Peru that those exposed to massive earthquakes (in 1960 and 1970, respectively) still show a relative deficit in educational and labour outcomes many decades later. More worrying, the latter project also shows that children whose mothers were affected at birth also manage to complete fewer years of schooling.

When formal insurance or other safety nets are not available, the poor diversify their income sources to lower risk exposure. Typically, this may be done either through labour sector diversification locally or through emigration. Lynham, Noy and Page (2012) observe people migrating away from 1960 Tsunami in Hawaii, for example, but Brata, Groot and Rietveld (2014) identify only a temporary change in population in response to the 2004 tsunami and the Nias earthquake in 2005 in Indonesia.[4] And indeed, research shows that remittances play an important role in the households reactions to disasters (Deshingkar and Aheeyarse 2006; Harvey and Group, 2007; Mohapatra et al., 2009; Savage et al., 2007). Suleri and Savage, 2006) observe that households receiving remittances are able to recover earlier from the 2005 Afghanistan earthquake. Gröger and Zylberberg (2015) observe rural household members in Vietnam migrating to urban areas in the aftermath of the 2009 catastrophic typhoon, and households with settled migrants receiving more remittances in the typhoon's aftermath. Le de, Guillard and Friesen (2014) observe an unequal access to remittances, with the poor having less access and therefore struggling more to recover from the 2012 cyclone in Samoa.

3. The Aftermath of the 2004 Tsunami in Sri Lanka

In the immediate aftermath of the 2004 catastrophe, the government established the Centre for National Operations (CNO) with special powers to oversee the coordination of agencies involved in rescue and relief. Three task-forces; (1) The Task Force for Rescue and relief (TAFRER); (2) The task Force for Logistics, Law and Order (TAFLOL) and (3) the Task Force for Rebuilding the Nation (TAFREN) were set up to address specific aspects of the relief effort (Government of Sri Lanka, 2005).

[4] This temporary effect may be due to the strong positive influence of the disaster on the peace deal between the Government of Indonesia and the Free Aceh movement in 2005. Halliday (2012) reveals people migrating away after an earthquake in El Salvador.

The Ministry of Finance set up a coordination system with national agencies, donor agencies, and international non-governmental organisations, to support 16 primary interventions or activities identified as priorities. The coordination and facilitation roles implementing reconstruction were eventually transferred to a newly formed Reconstruction and Development Agency (RADA). Reconstruction activities were coordinated at District and Division level by the Government Agent at each level (Post Tsunami Reconstruction and Recovery, Joint Report of GOSL and Development Partners, 2005).

Initially, the government declared a development-free buffer zone along the coast restricting reconstruction, but later in 2005 this policy was abandoned due to strong opposition from the public (Ingram et al., 2006). New houses were provided based on proven ownership claims for destroyed houses or, alternatively for those unable to claim land ownership, through a donor-driven program. For completely damaged houses, the government provided land and cash grants and additional donor assistance to rebuild houses. For partially damaged houses, cash grants were provided. Financing for tsunami reconstruction in Sri Lanka relied mainly on foreign grants. A total of 3.9 billion USD was committed; of which 2.0 billion came from foreign grants and 0.9 billion each from foreign loans (mostly multilateral) and the government of Sri Lanka. Almost 1.4 billion were spent on reconstruction already by the end of 2006 – two years after the tsunami (Jayasuriya and McCawley, 2010). Later, the tsunami reconstruction was managed within the mainstream development program. Despite very large flows of relief and reconstruction funds, reconstruction in Sri Lanka faced problems of coordination, escalation of construction costs, and other similarly common difficulties in post-disaster recoveries (Athukorala, 2012; Jayasuriya and McCawley, 2010; Munasinghe *et al.,* 2007).

4. Empirical Analysis of Household Survey

This study isolates the causal effect of the 2004 tsunami in a quasi-experimental analysis using pooled cross-sections of information from household surveys. We include observations of 84,303 households obtained in five Household Income and Expenditure Survey waves conducted in 1995, 2002, 2006, 2009 and 2012 by the Sri Lanka Department of Census and Statistics. The longitudinal nature and richness of household level information covering nearly a decade before and a decade after the tsunami make these surveys well suited to investigate the tsunami's long-term impact at the household level.

The surveys collected detailed information on household and individual demographics, employment, consumption, income and other related data corresponding to the preceeding calendar year. The demographic characteristics include variables such as sex, age, marital status, ethnicity, religion, level of education, employment status, house ownership; household food consumption (including in-kind consumption), household non-food expenditure (household expenditure on housing, education, health, transport, recreation, household expenditure on durables and on insurance and savings; the income of the household (from paid employments, non-agricultural and agricultural activities); cash receipts (pension, disability and relief, food stamp, property rent, dividends); and remittances (from abroad and from within the country).

Due to the civil conflict that ended in 2009, the data for eight districts out of total 25 districts are not available before the end of the conflict. Thus, survey data for 17 Districts from 1995 to 2013 were used in the analysis. Details about the data available in each wave of the household survey and their definitions are available in Appendix Table 1. The summary statistics are available in Table 1. The composition of ethnic and religious groups, and composition of households according to their location (urban, rural, estate) in the survey sample are all comparable approximately to the national figures available from the census, and the sample was collected, in principle, to be nationally representative.

To isolate the causal effect of the disaster precisely, randomised experimentation is ideal, and a (time-series) panel of households would be preferable. Since randomised experimentation is impossible and panel data are unavailable, we instead use cross-sectional data pre- and post-disaster in a quasi-experimental analysis. The identification strategy relies on the standard common trend assumption in difference-in-difference estimations, and we show that this assumption appears appropriate in this case.

To identify the treatment group, we exploit the spatial variation of tsunami damage using reported deaths, displacements, homelessness and infrastructure damage (replacement cost) due to tsunami across districts. Our aim is to reveal the average causal effect from the area-wide tsunami shock. Out of 25 Districts, 13 Districts were affected by the tsunami (Appendix Table 2) and reported mortality rates, the number of people displaced, the number of people that became homeless, and the damage to public infrastructure. Out of the 13 affected districts, the HH survey covered only seven districts both before and after the tsunami, as the other six districts were directly involved in the conflict. Our treatment group comprises the households in the affected seven districts for which we have data.

In the absence of household level reported tsunami damage, we first estimate the average effect for all households in the affected districts. However, the exposure of the districts and the households in those districts to the tsunami varied considerably. The regions on the eastern and southern coasts were directly exposed to the tsunami waves coming from east-south-east and higher damages were reported in those districts facing in that direction. We also exploit the damage information available across districts to examine how recovery vary when accounting for the level of damage. The district level reported deaths, displacements, homelessness, and the value of public infrastructure damaged are used as the proxies for exposure to the tsunami to identify the relative intensity of the shock across districts. We define a shock index by dividing the impact figures by the total number of households in the respective districts. We thus estimate a second model using a different treatment group: households in the three most highly affected regions (for which we have data): Galle, Matara, and Hambantota.

The previous literature argued that the long-term impacts vary with the vulnerability of the affected households (duPont and Noy, 2016). To examine the impact of vulnerability on recovery, we estimate two other models. One (Model 3) is estimated for a different treatment group excluding the two richest districts (Colombo and Gampaha) and the other (Model 4) for a treatment group including only the two richest districts excluded in Model 3. To further examine the sensitivity of our results, we investigate whether the causal effect depends on the type of damage. We estimate models using three disaster index variables: displacement, homelessness, and deaths.[5]

Our identification uses difference-in-difference (DID) method. The standard empirical specification is:

$$Y_{idt} = \beta_1 + \beta_2 Post_i + \beta_3 T_d + \beta_4 Post_i T_d + U_{idt} \quad (1)$$

[5] We exclude the infrastructure index, as it is highly correlated with displacement and homelessness.

Modifying the standard model, our empirical specification takes the following.

$$Y_{idt} = \beta_1 + \beta_2 Post_i T_d + \beta_3 \delta_t + \beta_4 X_{idt} + \beta_5 \gamma_d + U_{idt} \qquad (2)$$

Y_{idt} is the outcomes of interest- household monthly consumption and household monthly income- and; the unit observed is household *i,* in district *d* and time t. T_d is the treatment dummy defining membership in treatment cross section (affected=1, not affected=0) and U_{idt} are the unobserved affects. $Post_i$ is a dummy variable to distinguish sample by pre and post treatment (post-tsunami =1, pre-tsunami=0). β_2 is the treatment effect of interest.

Other than the common trend assumption, treatment exogeneity is a key for unbiased estimation. Treatment effects are naturally heterogeneous across households depending on household characteristics and the community level characteristics that they live in. By adequately controlling for such heterogeneity, the unobserved variation ideally should account for the average causal effect. Household demographic and socio-economic covariates X_{idt} are incorporated into the model to control for household heterogeneity. Gender (male=1, female=0), age (years), years of education, head of household employment status (binary variables for employed, unemployed and employed in paid occupation), household's ethnic group (binary indicators), and house ownership (binary) are all used in the model estimation. Pre shock differences of the treatment and control group that could be due to different time trends are controlled by year fixed effects (δ_t). The geographic differences are controlled by district fixed effects (γ_d) ; these therefore control for the $Post_i$ and T_d in eq. 1, respectively. Finally, the other differential effects and the mean of the error term U_{idt} are assumed zero. We estimate model 1-4 using this specification.

In a different set of regressions, instead of dummy variable for treatment as in the previous model (eq. 2), we introduce treatment indices (T_d^{ind}) into the model. Separate treatment index variables are used for death, displacement and homelessness.

$$Y_{idt} = \beta_1 + \beta_2 T_d^{ind} + \delta_t + X_{idt} + \gamma_d + U_{idt} \qquad (3)$$

The models are estimated using OLS. Since heteroscedasticity and serial correlation may be present in the data, we use robust and district clustered standard errors for inferences.

5. Results

We rely on several waves of the national household survey conducted by the Sri Lankan government. Table 1 provides some descriptive statistics of this data. In total, 64% of the observations are of households in the years following the tsunami, while 51% of the households live in the districts affected by the tsunami – 33% are of households in the tsunami areas observed in the aftermath. In some of the estimations, we include covariates that are also correlated with income or consumption. The details about these, and the regression results for the two dependent variables, income, and consumption are provided in the online appendix.

5.1 Income

Table 2 presents our benchmark results for household income. We observe the average treatment (tsunami) effect (ATE) on household income by examining the coefficient (β_2 in equation 2) for the interaction of the treatment indicator (tsunami-affected district), and post-tsunami year. Columns I-V present several estimations based on different assumptions regarding the standard errors and the inclusion of district fixed effects and district year trends. Column II controls for household heterogeneity; and district fixed-effects are included in column III. The inclusion of district fixed-effects reduces the size of the estimated ATE coefficients, suggesting that some of the observed ATE in column II is an over estimation associated with the higher income in the coastal districts. Column IV includes district-year interactions, but these over-fit the model, and remove much of the impact we associate with the tsunami itself (as our identification of treatment relies on households residing in a tsunami-affected district). Column V is our preferred specification as it includes district clustered standard errors, though results there are not dramatically different from the other specifications.[6]

To further examine the validity of our findings, we estimated the log-normal model using the log transformation of the dependent variables (income and consumption). The kernel density plot of residuals with normal density overlaid on the plot (in the online appendix)

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[6] The one exception is column IV that includes district-specfic time interactions. Since we only have a few observations post disaster, and our identification relies on cross-district differences, the inclusion of this term incorporates much of the identified tsunami impact.

show slightly skewed error distribution. The inter-quartile range test (results available in online appendix) shows the presence of 3-4% outliers in the non-log model. Results available in the online appendix also show that the log-normal model rectifies this issue (these estimates are shown in table 6 column I).[7]

Table 2, column V (with robust and clustered standard errors) shows the causal effect (ATE) of the tsunami impact on household income. The results indicate a positive average effect on household income in affected districts. Income increased due to the tsunami in the year 2006 by Rs. 7067 (47 US$), slightly reduced in the year 2009 (Rs. 5872, 39.14 US$) and increased significantly in the year 2012 by Rs. 15003 (100 US$). The effect is clearly seen in the normalised income (the predicted residuals regressing income against household covariates and district fixed effects and collapsed by mean and survey years for both control and treatment groups) in figure 1.

In figure 1, the two parallel lines for treatment and control group before tsunami clearly indicates the absence of different income trend between treatment and control group pre-tsunami and appears to confirm that our common-trend assumption is valid. The divergence of the two lines in the figure post-tsunami starkly demonstrates our finding: households residing in tsunami affected districts experienced an increase in income in post-tsunami years.

The same model as in column V of table 1, when estimated for the treatment group of the most-affected regions (column VI), reveals a much more moderate income increase shortly after the tsunami - Rs. 2045 in 2006. This effect, compared to an increase of more than three times as much for all affected regions, suggests that the districts that benefited the most were those that were perceived as tsunami affected (and therefore received assistance) but were less heavily damaged. In the longer-term, in the 2009 and 2012 observations, the estimated impact of the tsunami on household income for heavily affected regions becomes negative (but statistically insignificant); compared to large and

[7] Log tranformations create other issues. Income data has considerable zero and negative observations and log transformation drops those observations (column I of table 6). Another model is estimated using log-modulus transformation (John and Draper, 1980) to preserve the sign and zero observations (column II of table 6). Nevertheless, the log transformation drastically changes the distribution of of the dependent variable. Extreme values are obviously possible in our data since we use time series data with 15 years time gap. This is evident in the scatter plots of log and non-log income and consumption in online appendix. Given that the change in distribution can significantly affect the average income and consumption and ATE in each year, which our main variable of interest in identifying the causal effect.

significant positive impact on all affected districts. Again, this suggests the role that assistance played in recovery, with less affected districts benefiting the most.

Column VII estimated the same model but excluded the two richest regions (one of them is the capital, Colombo). Maybe not surprisingly, in that case as well, we see a much more moderate increase in the positive impact of the tsunami recovery on household income. Again, this difference is most likely associated with the increased access to post-tsunami assistance for the two richest (and urban) regions that were now excluded. Confirmation of that is found in column VIII, where the model estimated focuses on the ATE for the richest two regions. The identified ATE is 3-5 times as large for the richest as for the poorest affected regions (column VII).

In table 3, we describe the ATE on the various sources of household income. In particular, we separately examine the ATE for paid income, agricultural income, remittances, transfers, dividends, and rents (and other income). We estimate these using the same specification as in table 2 column V – our preferred specification. In all the different income sources, the identified ATE for the three post-tsunami years is positive, though the estimated coefficient is often not statistically significant. The increase in monthly income from non-agricultural activities is the largest, and also the most statistically significant: in 2006 by Rs. 4559 (31.4 USD), in 2009 by Rs. 3911 (27.0 USD) and 2012 by Rs. 6246 (43.1 USD). As in the table 2, we observe more moderate increases in income in the immediate aftermath, and a larger impact observed in the 2012 survey. In most of the households' income streams, the increase in the 2006 and 2009 is not statistically different from zero (no treatment effect) but it is statistically significant and positive for 2012. We also observe that not only do we identify the biggest ATE for non-agricultural income, the model's goodness-of-fit is best for that income source. Our ability to determine the cross-household differences in other income sources is much more limited, and the observed tsunami impact (ATE) is in any case much smaller for these. However, the impacts described in table 3 are the ATE averaged over all affected regions, and the districts were exposed to the tsunami in varying degrees. Results by district (online appendix) show that household in all affected regions except Puttlam experienced increase of income and the positive impacts persisted into the 2012 survey. Figure 2 illustrates the variation of impact among the affected districts.[8] We note

[8] Conversion of Sri Lankan Rupees to USD is based on the August 2016 exchange rate of 1USD=145 Rs.

that the 2006 survey was conducted less than two years after the tsunami disaster and 2009 marked the most intense fighting between the government and the LTTE, just before the conflict ended in 2010. These observations suggest that our finding that income increased more in 2012 may be quite intuitive. When examining districts separately, we find that Colombo (CMB) and Gampaha(GMP) have significantly higher incomes; while most other districts either have lower income post-tsunami or no observed change.

5.2 Consumption

Tables 4 and 5 include the detailed estimation of the impact of the tsunami on household consumption and its components, respectively. As discussed above with respect to income, our preferred specification in column V of table 4 includes the household covariates and the district fixed-effects, and is estimated with district clustered standard errors. In column V, the estimated ATE for consumption is positive in the three years post tsunami for which we have a measurement, but is statistically significant only for the immediate aftermath, and for the longer term (in 2012). As was the case for income, the impact in the longer term (2012) is larger than the impact in the immediate aftermath. Importantly, however, the positive observed increase in consumption is much smaller than the increase we identified in household income. It appears that the increase in income does not translate very well into increases in welfare (consumption).

As we observed that the increase in income was much smaller for the most heavily damaged districts (column VI in table 2), we observe that the same districts did not experience an increase in income but rather appeared to have experienced a decrease in consumption (though the decrease is not statistically significant – see column VI in table 4). The difference between the two richest regions and the rest of the affected regions is less stark for consumption than it was for income, but we still observe a bigger increase in consumption in the richest districts than we observe for the other affected districts in the longer term (columns VII and VIII in table 4).

The normalised income is presented in figure 3 (predicted residuals when regressing consumption against household covariates and district fixed effects are collapsed by mean and survey years for both control and treatment groups). The figure depicts the parallel consumption trends before the 2004 tsunami, and the steeper increase in consumption observed for the treated (impacted) districts. At the district level (results in the online appendix), we find temporary gains for Matara and Gall; persistent gains for Kalutara, Gampaha, Hambantota, Colombo and Puttlam. Figure 4 illustrates the variation of impact across the impacted districts.

The surveys we use include details questions about expenditure patterns, so we use the same diff-and-diff methodology to identify ATE for each component of expenditure (table 5). When distinguishing between food and non-food expenditures, we find that, worryingly, food consumption actually decreased in the affected districts as a consequence of the tsunami, while non-food consumption increased (and that accounts for the overall increase identified in table 4). Especially notable is the decrease in food consumption observed in 2009 (column I table 5), after the inflow of external assistance has ebbed five years after the tsunami. When we examine the separate components of non-food consumption we find, overall, increases in all of the items, with the largest identified increase in, not surprisingly, housing – an increase that is probably related to the cost of reconstruction and the increase in construction costs that is typical of most disaster recoveries. [9]

6. Robustness Analyses

In tables 2-5, we found that the tsunami and the ensuing inflow of assistance significantly increase household income, but that consumption gains were much more limited. What explains these lack of 'pass-through' from income to consumption is not immediately obvious. Some expenditure and income components are missing in our data – most relevant seem investment in property. Due to inconsistent survey questions across surveys, all income and expenditure components are not available in our complete time series dataset. Therefore, the average household consumption is approximately Rs. 3000 higher than the average household income reported in our summary statistics (Table 1). In order to provide more information on the 'missing income,' we exclude the year 2002 survey (the survey wave with most missing components) and repeated the analysis while including ad-hoc income. These regressions are available from the authors, but they clearly, and similarly,

[9] Non-consumption expenditures (column X) include the expenses on household security and payment of liabilities (savings, payment of tax, thrift societies, debt payment etc.).

show a positive impact on income and consumption. Still, we again observe income increases to be substantially bigger than the identified consumption increases.

In table 6, we reestimate the key equations using log income (column I and II) and log consumption (column III). Results are similar to the results we previously obtained in the benchmark estimations in column V in table 2 and column V in table 4 for income and consumption, respectively. We see an increase in consumption that is significantly higher than the observed increase in consumption (which in even negative in column III).

Subsequently, in table 7, we aim to account for the relative intensity of tsunami damages in each district. The tsunami's impact is measured separately by deaths, displacements, and homelessness. Comparing the regressions modelling consumption (columns I-III) and those modelling income (columns IV-VI) reveal, again, that there is little pass-through from increases in post-tsunami income to post-tsunami consumption. What we observe is that the intensity of damages is correlated with more income (probably because there are higher assistance flows/aid) but with less consumption.

In addition, we estimated the diff-in-diff model with "affected households and pre-disaster 2002-year interaction variable" as a type of placebo test. When 'pretending' that the tsunami occurred in 2002, we verify that the income and consumption of treatment and control group were not significantly different before the disaster event. We find ((results available upon request) non-significant ATE for both outcome variables (income and consumption). The treatment and control groups are not different in their income and consumption before the tsunami; providing additional evidence to support the validity of our results.

The causal effect we find could also be biased if the tsunami caused affected households to migrate, thus changing the sample dramatically. Given the reconstruction policy process in Sri Lanka whereby land was allocated nearby to the areas of destruction, we argue that migration after the disaster should have been negligible. In order to verify this claim, we examined the net migration of affected districts between 1982 and 2012 (online appendix). We indeed find that people migrated away from the affected regions of Matara, Galle, and Hambantota districts and migrated into tsunami affected Colombo, Gampaha, Kaluthara and Puttlam districts. Considering the overall migration pattern in Sri Lanka, most people migrated into the tsunami affected coastal and urban areas. It is most likely that migrants out from Matara, Galle and Hambantota settled in tsunami-affected Colombo, Gampaha or Kaluthara districts.

7. Conclusion

Few research projects attempt to identify and quantify the long-term impact of a catastrophic disaster on household wellbeing. Most research attention is usually directed to an event in its immediate aftermath, and interest eventually wanes. From a macroeconomic perspective, the majority of the evidence points to no-effect at the national level and more adverse local long-term effect. Yet, little is really known about the impacts at the micro/household level in the longer term. Here, we estimated the causal effect of the Indian Ocean tsunami in Sri Lanka on household income and consumption eight years after the event, using a quasi-experimental method.

A strong association between area-wide tsunami disaster shock and increases in household income and consumption in the long-term emerged from our empirical investigation. Deviating from the common observation in the literature on short-term impacts, these results are suggestive of an optimistic potential for long-lasting positive consequences. Nevertheless, our analysis does not provide any evidence to evaluate whether the observed positive effect is due to so-called 'creative destruction' – the replacement of old with new capital and technology. Sri Lanka received a very large amount of external transfers post-tsunami, much larger than is typical for disaster events (Becerra et al., 2014 and 2015). The increases in consumption and income can thus be associated not with a 'build-back-better' reconstruction, but purely due to the infusion of unusually massive amounts of external resources for rebuilding. This infusion is not replicable in other cases, and only an accounting for the amount of assistance received, per district, could possibly start to allow us to differentiate between these two hypotheses.

Our findings suggest a more nuanced picture with respect to household consumption impacts. We observe a reduction of food consumption and only find an increase in non-food consumption. The increase in non-food consumption is much smaller than the increase in income. As previously observed in the literature, it is clearly evident that households in high-income regions experience better recovery from disaster. The positive impact on income is largely ‘enjoyed’ by the higher income regions. Household consumption follows a similar pattern. As was the case more generally, it is impossible to know, at this point, whether the most dramatic increases in incomes and consumption in the wealthier regions was due to their better resilience (and reduced vulnerability) or a function of their improved ability to capture the inflows of aid into the affected regions. After all, both of these possibilities have been documented in research projects on short-term post-disaster dynamics.

Further improvements to the analysis remain. More rigorous analysis can be obtained by incorporating more variation of the shock using smaller geographical units. This may address possible errors generated by the method used to identify the shock in the present approach. An evaluation of the plausibility of “creative destruction” hypothesis can also be undertaken by controlling for external financing; which we were unable to do with the available data in this case. Understanding and identifying the distributional impact of the tsunami is also a policy-relevant question we plan to pursue.

Table1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Sex (Household head)	84303	.79	.42	0	1
Age (Household head)	84303	51	14.04	10	99
Education(Yr) (HH head)	84303	7	2.94	0	18
Ethnic grp. Sinhalese	84303	.85	.35	0	1
Ethnic group-Tamil	84303	.14	.35	0	1
Other ethnic	84303	.00	.06	0	1
Religion-Buddhist	84303	.79	.40	0	1
Religion-Hindu	84303	.07	.25	0	1
Religion-Muslim	84303	.06	.24	0	1
Religion-Catholic	84303	.07	.26	0	1
Other Religion	84303	.00	.01	0	1
Married (Household head)	84303	.80	.40	0	1
Wid./Devorced (HH head)	84303	.18	.38	0	1
Not married (HH head)	84303	.02	.15	0	1
Household size	84303	4	1.88	1	20
House ownership	84303	.79	.40	0	1
Total cultivated land (Perch)	84303	102	759	0	128003
HH in rural sector	84303	.81	.39	0	1
HH in urban sector	84303	.13	.34	0	1
HH in estate sector(Dummy)	84303	.05	.22	0	1
HH head employed	84303	.57	.49	0	1
HH head un employed	84303	.03	.16	0	1
HH head employed in non-paid occupation	84303	.34	.47	0	1
HH receiving transfer payments	84303	.28	.45	0	1
HH receiving Pension and disability payments	84303	.10	.30	0	1
HH receiving Remittance-local	84303	.07	.26	0	1
HH receiving Remittance-Foreign	84303	.07	.26	0	1
HH receiving transfer payments (Rs)	84303	142	377	0	30000
HH receiving –Pension and disability payments (Rs)	84303	959	4418	0	156000
HH receiving Remittance-local (Rs.)	84303	4439	33520	0	2400000
HH receiving Remittance-Foreign (Rs.)	84303	7790	52799	0	2050000
HH - After Tsunami	84303	.64	.48	0	1
HH affected by Tsunami	84303	.51	.50	0	1
Affected HH observed after Tsunami	84303	.33	.47	0	1
Income (Rs./month)	84303	8536.23	12497	-3595	98732
Consumption (Rs./month)	84303	11692.86	10584	297	87436

Table 2: Impact of tsunami on Household Income

Models		Average effect of affected regions				Regions with high intensity	Without richest regions	Richest regions
Independent Variables	(I) Robust S. E	(II) Robust S. E	(III) Robust S. E	(IV) Robust S. E	(V) District Clustered Robust SE	(VI) District Clustered Robust SE	(VII) District Clustered Robust SE	(VIII) District Clustered Robust SE
year_2002	No	-700 (95) ***	-361 (92) ***	774 (334) **	-361 (484)	261 (214)	-389 (262)	-590 (586)
year_2006	No	-1879 (121) ***	-105 (100)	-818 (70) ***	-105 (1245)	2791 (461) ***	-127 (1241)	-239 (1270)
year_2009	No	-3185 (94) ***	-664 (80) ***	1648 (381) ***	-664 (861)	2198 (160) ***	-690 (848)	-804 (886)
year_2012	No	-1319 (164) ***	1476 (137) ***	-717 (100) ***	1476 (1791)	11334 (543) ***	1418 (1800)	1101 (1854)
Treatment*2006	6878 (214) ***	10972 (212) ***	7067 (195) ***	4985 (373) ***	7067 (2421) ***	2045 (420) ***	2711 (1573) *	11766 (1845) ***
Treatment*2009	5057 (186) ***	10440 (168) ***	5872 (165)	3832 (578) ***	5872 (1674) ***	-412 (326)	2882 (1245) **	9259 (1095) ***
Treatment*2012	16005 (248) ***	18892 (252) ***	15003 (224) ***	-2239 (178) ***	15003 (3997) ***	-418 (888)	8068 (3172) **	22981 (2917) ***
Treatment	4400 (89) ***							
Pre tsunami	-528 (67)	No	No	No	No	No	No	No
Household covariates	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
District year trend	No	No	No	Yes	No	No	No	No
constant	3448 (56)***	4883 (818) ***	-896 (782) ***	936 (758)	-896 (1082)	352 (999.02)	26 (939)	-542 (1103)
F		898.47	1802.73	775.21				
R-squared		0.29	0.41	0.53	0.49	0.24	0.3946	0.55
Number of observations		84303	84303	84303	84303	55921	65921	58827

Table 3: Impact of tsunami on household Income by source of income

Income sources Independent Variables	Paid income	Agricultural Income	Non-agricultural Income	Remittance	Transfers	Dividends	Rents and other income
year_2002	638 (312) **	280 (317)	-1599 (634) **	45 (35)	36 (58)	26 (11) **	305 (113) ***
year_2006	599 (1054)	-96 (171)	-1083 (333) ***	171 (94) *	13 (31)	10 (10)	298 (113) ***
year_2009	67 (735)	-34 (171)	-1073 (331) ***	147 (77) *	11 (52)	6 (5)	232 (85) ***
year_2012	1760 (1518)	59 (196)	-990 (345) ***	338 (162) **	137 (77) *	6 (7)	185 (77) **
Treatment*2006	1786 (1098)	231 (286)	4559 (1750) ***	93 (110)	175 (55.53) ***	12 (22)	177 (142)
Treatment*2009	940 (765)	325 (220)	3911 (1470) ***	136 (93)	62 (52)	33 (15) **	428 (178) **
Treatment*2012	5673 (1869) ***	717 (326) **	6246 (2202) **	947 (257) ***	828 (168) ***	110 (42) ***	447 (122) ***
Household covariates and District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
constant	-906 (723)	-29 (216)	952 (371) ***	-124 (81)	-9 (88)	-14 (15)	-91 (94)
R-squared	0.33	0.12	0.24	0.05	0.08	0.01	0.03
Number of observations	84303	84303	84303	84303	84303	84303	84303

Notes: Robust standard errors in bracket. *, **, *, stand for significance at 1%, 5% and 10% respectively. No district year trends**

Table 4: Impact of tsunami on Household consumption

Models	Average effect of affected regions					Regions with high intensity	Without richest regions	Richest regions
Independent variables	(I) Robust S. E	(II) Robust S. E	(III) Robust S. E	(IV) Robust S. E	(V) District Clustered Robust SE	(VI) District Clustered Robust SE	(VII) District Clustered Robust SE	(VII) District Clustered Robust SE
year_2002	No	-2618	452	1232	452	261	388	581
		(154)***	(72)***	(197)	(205)***	(214)	(243)	(158)***
year_2006	No	-1335	2829	2846	2829	2791	2849	2897
		(136)***	(131)***	(566)	(445)***	(461)**	(452)***	(449)***
year_2009	No	-2548	2236	2735	2236	2198	2255	2304
		(159)***	(100)***	(330)	(175)***	(160)**	(170)***	(180)***
year_2012	No	6696	11140	10686	11140	11334	11424	11041
		(213)***	(185)***	(519)	(567)***	(543)**	(548)***	(600)***
Treatment*2006	-1902	4144	1269	1555	1269	2045	1686	877
	(172)	(158)***	(192)***	(696)	(507)***	(420)**	(457)***	(703)
Treatment*2009	-3588	2964	207	1070	207	-412	-58	492.
	(164)***	(118)***	(161)	(454)	(275)	(326)	(318)	(247)**
Treatment*2012	8309	5697	2786	2167	2786	-418	1241	4560
	(211)***	(240)***	(239)***	(796)	(1103)***	(888)	(1237)	(725)***
Treatment	3284	No	No	No	No	No	No	No
	(75)***							
Pre Tsunami	-5577	No	No	No	No	No	No	No
	(88)***							
Household covariates	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
District year trend	No	No	No	Yes	No	No	No	No
constant	11771	3735	-428	869	-428	352	3380	2458
	(80)	(744)***	(744)	(743)	(1083)	(999)	(612)***	(1449)*
F	2894.63	771.33	554.05	231.36				
R-squared	0.19	0.25	0.28	0.29	0.28	0.24	0.1623	0.30
Number of observations	84303	84303	84303	84303	84303	55921	66246	58827

Notes: Robust standard errors in bracket. *, **, *, stand for significance at 1%, 5% and 10% respectively.**

Table 5: Impact of tsunami on Household consumption by type of consumption

Dependent var. / Independent var.	Food cons (I)	Non-food cons. (II)	Housing (III)	Clothing (IV)	Personal care (V)	Comm. & transp. (VI)	Education (VII)	Health (VIII)	HH non-durables (IX)	Non-cons. Expenditure (X)
year_2002	-942 (184)***	1391 (197)***	267 (56)***	-237 (33)***	17 (5)***	187 (31)***	69. (12)***	60 (12)***	-18 (8)**	948 (101)***
year_2006	-253 (174)	3085 (401)***	637 (70)***	806 (28)***	40 (7)***	604 (46)***	180 (19)***	91 (24)***	-10 (9)	1192 (205)***
year_2009	-592 (135)***	2831 (140)***	396 (27)***	66 (23)***	38 (4)***	657 (52)***	160 (11)***	73 (14)***	-11 (6)*	1211 (85)***
year_2012	2728 (214)***	8414 (453)***	2178 (168)***	385 (29)***	219 (8)***	1717 (109)***	531 (36)***	377 (50)***	81 (8)***	2444 (193)***
Treatment*2006	-274 (155)*	1552 (439)***	285 (116)**	18 (23)	8 (8)	303 (86)***	61 (22)***	103 (34)***	4 (9)	742 (211)***
Treatment*2009	-538 (120)***	761 (274)***	273 (160)*	-67 (22)***	-.3 (8)	99 (72)	125 (40)***	109 (29)***	-14 (7)**	329 (164)**
Treatment*2012	-141 (252)	2897 ((928)***	985 (558)*	3 (23)	45 (26)*	374 (245)	256 (108)**	243 (57)***	-12 (9)	974 (468)**
Household covariates and District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District year trend	No	No	No	No	No	No	No	No	No	No
constant	3025 (222)***	-3432 (771)	-823 (392)**	97 (14)***	-5 (9)	-770 (185)***	-262 (64)***	-167 (76)**	40.39796 (4)***	-1325 (153)***
R-squared	0.27	0.23	0.29	0.16	0.27	0.12	0.06	0.03	0.12	0.07
Number of observation	84303	84303	84303	84303	84303	84303	84303	84303	84303	84303

Notes: Robust standard errors in bracket. *, **, *, stand for significance at 1%, 5% and 10% respectively.**

Table 6: Impact on consumption and income using log of income and consumption (log normal)

Dependent variables / Independent variables	Log of income I	Log of income II	Log of Monthly consumption III
year_2002	-.31 (.25)	-1.76 (.45)***	.048 (.026)*
year_2006	-.87 (.43)**	-3.3 (1.39)**	.32 (.05)***
year_2009	-2.01 (.84)**	-1.17 (.84)	.27 (.02)***
year_2012	-1.47 (.86)	-.73 (.84)	.98 (.03)***
Treatment*2006	1.32 (.54)**	3.20 (1.48)**	.03 (.06)
Treatment*2009	2.27 (.96)**	1.23 (.96)	-.05 (.02)**
Treatment*2012	2.4 (.97)**	1.45 (.95)	-.08 (.04)**
Household covariates	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
District year trend	No	No	No
Constant	5.68 (.59)***	5.68 (.59)***	7.97 (.045)***
R-squared	0.78	0.74	0.35
N. of obs.	71234	84303	84303

Notes: Column I dropped all observations for whom the dependent variable ≤0.While column two includes them (by adding a small constant. Robust standard errors in the bracket. ***, **, *, stand for significance at 1%, 5% and 10% respectively.

Table 7: Consumption and income consequences by type of damage

Dependent variables	Consumption			Income		
Independent Variables	Death	Displacement	Homelessness	Death	Displacement	Homelessness
year_2002	465. (208) **	463 (209)	462 (209)	-264 (510)	-260 (513)	-261 (519)
year_2006	3276. (282.) ***	3231 (260)	3047 (280)	3664 (2018)	3276 (1953)	2924 (1992)
year_2009	2388 (204) ***	2429 (193)	2431 (191)	2275 (1523)	2011 (1477)	1686 (1510)
year_2012	12738 (649) ***	12752 (625)	12675 (624)	8917 (3627)	8375 (3459)	7462 (3494)
Treatment*2006	84313 (23367) ***	4642 (1383)	12250 (2971)	-51074 (103401)	5190 (6525)	18628 (16751)
Treatment*2009	-21425 (24075)	-1874 (553)	-2976 (2114)	3145 (76281)	5530 (5485)	18367 (13663)
Treatment*2012	-71482 (73629)	-3615 (3341)	-3178 (10143)	111721 (180436)	16042 (14300)	52080 (34625)
Household covariates	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
District year trend	No	No	No	No	No	No
constant	-851 (1084)	-883 (1065)	-839 (1043)	-3419 (1534.30)	-3125 (1495)	-2770 (1538)
R-squared	0.28	0.28	0.28	0.44	0.44	0.44
Number of observations	84303	84303	84303	84303	84303	84303

Notes: Robust standard errors in bracket. *, **, *, stand for significance at 1%, 5% and 10% respectively.**

Figure 1: Normalised income of affected and non-affected households

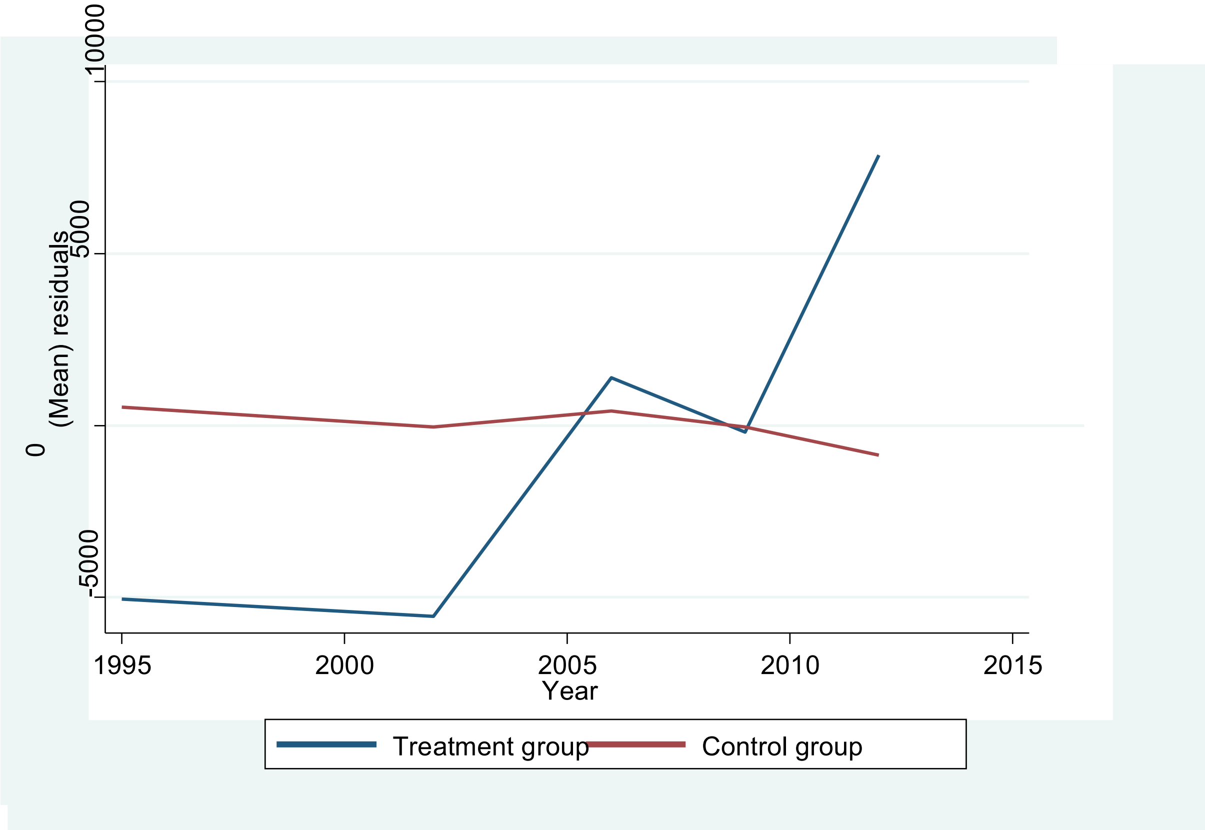


Figure 2: Normalised income of affected households by districts

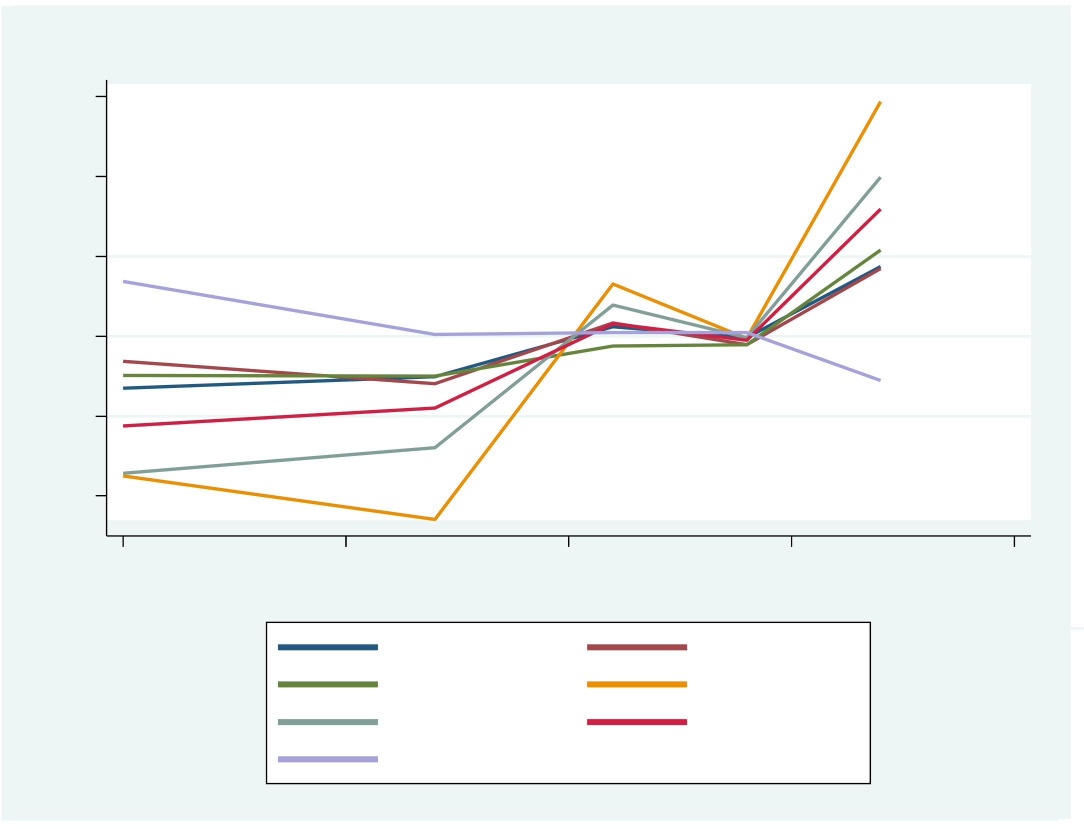


Figure 3: Normalised consumption of affected and non-affected households

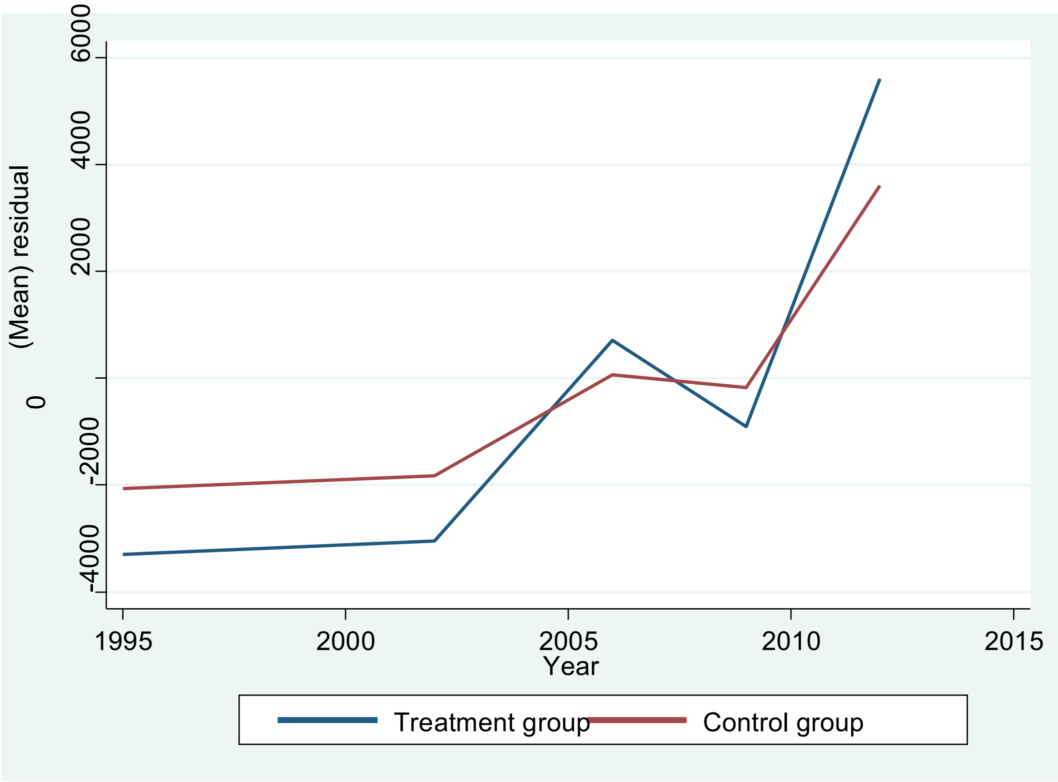
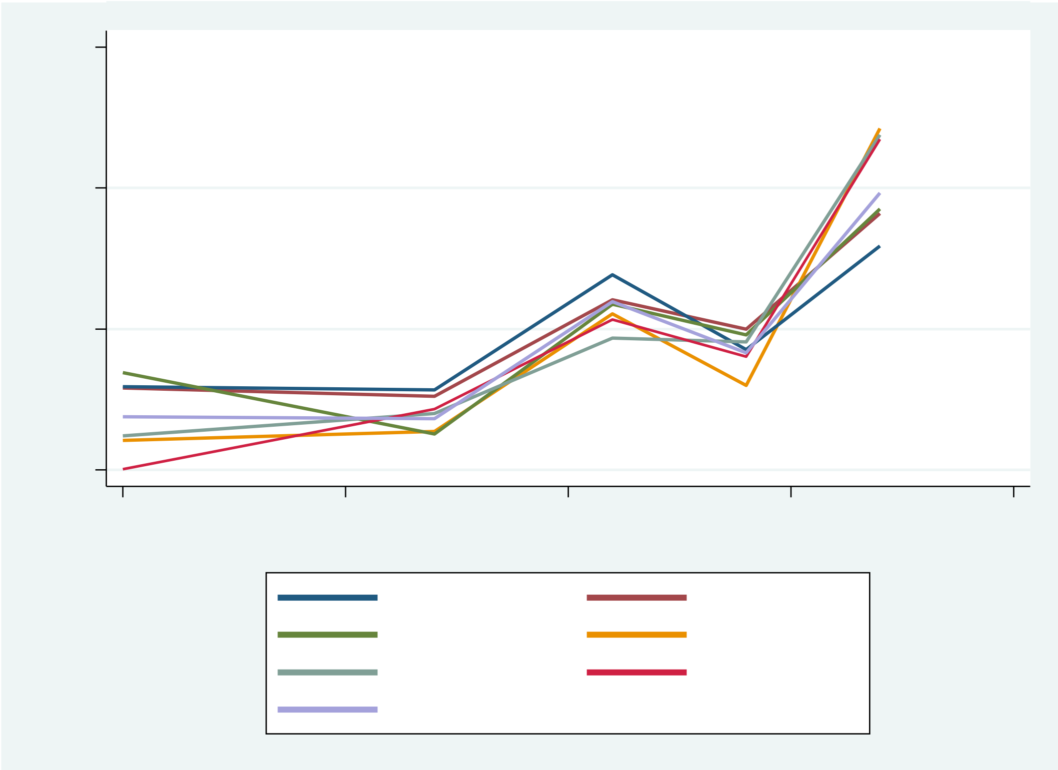


Figure 4: Normalised consumption of affected households by District



References

Aizenman, J., & Noy, I. (2015). Saving and the Long Shadow of Macroeconomic Shocks. *Journal of Macroeconomics*, *46*, 147-159.

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers 58*, 450-474.

Athukorala, P. (2012). Indian Ocean Tsunami: Disaster, Generosity and Recovery. *Asian Economic Journal*, *26*(3), 211–231.

Becerra, O., Cavallo, E., & Noy, I. (2014). *Foreign Aid in the Aftermath of Large Natural Disasters. Review of Development Economics, 18*(3), 445–460**.**

Becerra O, Cavallo E, Noy I (2015) Where is the Money? Post-disaster foreign aid flows. *Environ Dev Econ, 20*(5):561–586

Baez, J. E. (2006). Income Volatility, Risk-Coping Behavior and Consumption Smoothing Mechanisms in Developing Countries: A Survey. *Desarrollo y Sociedad, 58,* 37-83.

Baez, J. & Mason, A. (2008). *Dealing with Climate Change: Household Risk Management and Adaptation in Latin America, background paper for the 2008 World Bank Flagship Report on Climate Change in Latin American and the Caribbean*, Washington, DC: The World Bank. Retrieved from: http://dx.doi.org/10.2139/ssrn.1320666

Barrett, C.B., Marenya, P.P., McPeak, J., Minten, B., Murithi, F., Oluoch-Kosura, W., Place, F., Randrianarisoa, J.C., Rasambainarivo, J., & Wangila, J. (2006). Welfare dynamics in rural Kenya and Madagascar. *Journal of Development Studies, 42*(2), 248-277.

Bhalotra, S., Sanhueza, C., & Wu, Y. (2011). *Long-term economic consequences of the 1960 Chile earthquake. http://www.webmeets.com/files/papers/lacea-lames/2011/767/Paper_11Mayl2011.pdf*

Brata, A. G., Henri L. F. de Groot & Piet Rietveld, P. (2014). The Impact of the Indian Ocean Tsunami and the Nias Earthquake on the Spatial Distribution of Population in Northern Sumatra*. Bulletin of Indonesian Economic Studies, 50*(1), 101-121.

Carter M. R. & Barrett, C. B. (2006). The economics of poverty traps and persistent Smoothing and Asset Protection. *Journal of Development Studies 42*(2), 178-199*.*

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and the long-term consequences of natural disasters in Ethiopia and Honduras. *World Development, 35* (5), 835–56.

Caruso, G. & Miller, S. (2015). Long run effects and Intergenerational transmission of natural disasters: A case study on the 1970 Ancash Earthquake*. Journal of development Economics. 117*, 134-150.

Cochrane, H.C. (2004). Indirect Losses from Natural Disasters: Measurement and Myth*.* In: Yasuhide Okuyama and Stephanie E. Chang (Eds.), *Modelling the Spatial and Economic Effects of Disasters.* New York, NY: Springer.

Cuaresma, J. C. (2009). Natural Disasters and Human Capital Accumulation. (Policy Research Working Paper 4862)*.* The World Bank. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/4058/WPS4862.pdf

Central Bank of Sri Lanka (2015). *Socio economic data.* http://www.cbsl.gov.lk/pics_n_docs/10_pub/_docs/statistics/other/Socio_Econ_Data_2015_e.pdf.

Centre for Research on the Epidemiology of Disasters (CRED). *The human cost of natural disasters: A global perspective.* Retrieved from *http://cred.be/sites/default/files/The_Human_Cost_of_Nsatural_Disasters_CRED.pdf*

De Mel, S., McKenzie, D., & Woodruff, C. (2011). Enterprise recovery following Natural Disasters. *Economic Journal, 122*, 64–91.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption, and poverty traps: evidence from Ethiopia. *Journal of Development Economics, 96* (2), 159–73.

Dercon, S., Hoddinott, J. & Woldehanna, T. (2007). Growth and Poverty in rural Ethiopia. *Background Paper for the Chronic Poverty Report 2008-09.* Chronic poverty Research Centre.

Department of Census and Statistics. (2015). *District statistical handbook.* http://www.statistics.gov.lk/

Department of Census and Statistics. *Census of Population and Housing- final report 2013.* http://www.statistics.gov.lk/PopHouSat/CPH2011/Pages/Activities/Reports/FinalReport/FinalReport.pdf

Department of Census and Statistics (2005). *Report on Impact of Tsunami 2004 on Sri Lanka.* http://www.statistics.gov.lk/tsunami/census/Summarynew.pdf

Department of Census and Statistics*. Poverty Indicators: Household Income and Expenditure Survey - 2012/13.* Retrieved from http://www.statistics.gov.lk/poverty/PovertyIndicators2012_13.pdf

Deshingkar, P. & Aheeyarse, M. M. M. (2006) *Remittances in crisis Remittances in Sri Lanka after the tsunami*, Background paper to The Humanitarian Policy Group, UK: The Overseas Development Institute.

Government of Sri Lanka. (2005). *Post Tsunami Recovery and Reconstruction Strategy, May 2005.*

Gröger A, & Zylberberg Y. (2016). Internal Labour Migration as a Shock Coping Strategy: Evidence from a Typhoon. *American Economic Journal: Applied Economics, 8*(2): 123–153

Halliday, T. (2012). Intra-household labour supply, migration, and subsistence constraints in a risky environment: Evidence from rural El Salvador*. European Economic Review*, *56*(6), 1001-1019

Hallegatte S., Bangalore, M., Bonzanigo, L., Fay, M., Narloch, U., Rozenbuerg, J., & Vogt-Schilb, A, (2014). *Climate change and poverty: An analytical framework.* (Policy research working paper 7126). The World Bank. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/20639/WPS7126.pdf

Hallegatte, S. & Przyluski, V. (2010). The economics of natural disasters: Concepts and methods. (Policy research working paper 5507). The World Bank.

Hoddinott, J. (2006). Shocks and their consequences across and within households in Rural Zimbabwe. *Journal of Development Studies, 42*(2), 301-321, Ingram, J. C., Franco, G., Rumbaitis-del Rio, C, & Khazai, B. (2006). Post-disaster recovery dilemmas: challenges in balancing short-term and long-term needs for vulnerability reduction. *Environmental Science & Policy*, *9*(7–8), 607-613.

Janzen, S., & Carter, M. (2013) *After the Drought: The Impact of Micro insurance on Consumption.* (NBER Working Paper No. 19702).

Jaramilo, H. (2009). *Do natural disasters have long term effects on growth? Universidad de Los Andes,* Faculty de Economica. Retrieved from http://econpapers.repec.org/scripts/redir.pf?u=http%3A%2F%2Feconomia.uniandes.edu.co%2Fpublicaciones%2Fdcede2009-24.pdf;h=repec:col:000089:006647.

Jayasuriya, S., & McCawley, P. (2010). *The Asian tsunami: Aid and Reconstruction after tsunami.* Asian Development Bank institute, Cheltenham, UK: Edward Elgar Publishing.

John, J. A., & Draper, N. R. (1980). An alternative family of transformations. *Journal of the Royal Statistical Society, Series C (Applied Statistics) 29*(2), 190-197. DOI: 10.2307/2986305

Joint Report of GOSL and Development Partners (2005). *Sri Lanka Post Tsunami Reconstruction and Recovery.* Retrieved from *http://www.preventionweb.net/files/1591_9792.pdf*

Kazianga, H., & Udry, C. (2006). Consumption Smoothing? Livestock, Insurance and Drought in Rural Burkina Faso. *Journal of Development Economics*, *79*(2), 413-46.

Klomp J, Valckx K. (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change*, *26*, 183-195

Lazzaroni S, van Bergeijk P. (2014). Natural disasters' impact, factors of resilience and development: A meta-analysis of the macroeconomic literature. *Ecological Economics,107*, 333–346.

Le Dé L., Gaillard J.C., Friesen W. (2015). *Remittances and disaster: Policy implications for disaster risk management*. Migration, Environment and Climate Change Policy Brief Series 2/1. Geneva, Switzerland: International Organization for Migration.

Little, P.D., Stone, M.P., Mogues, T., Castro, A.P. & Negatu, W. (2006). 'Moving in place': Drought and poverty dynamics in South Wollo, Ethiopia*. The Journal of Development Studies, 42*(2), 200-225.

Lynham, J., Noy, I., & Page, J. (2012). The 1960 tsunami in Hawaii: Long term consequences of coastal disaster. (Working paper No12-16). Manoa: University of Hawaii.

McCarthy, C & Smith, S. K. (2009*).* Fleeing The Storm(s): An examination of evacuation behaviour during Florida's 2004 hurricane season. *Demography, 46*(1), 127–145.

Mechler, R., Linnerooth-Bayer, J., & Peppiatt, D. (2006*). Micro insurance for Natural disasters in developing countries: Benefits, limitations and viability.* ProVention Consortium, Geneva. Retrieved from: http://www.proventionconsortium.org/themes/default/pdfs/Microinsurance_study_july06pdf

Ministry of Disaster Management (2014), *Disaster Management Policy of Sri Lanka.* Retrieved from http://www.disastermin.gov.lk/web/images/pdf/sri%20lanka%20disaster%20management%20policy%20english.pdf

Mogues, T. (2011). Shocks and asset dynamics in Ethiopia. *Economic Development and Cultural Change*, *60*(1), 91-120.

Mohapatra, S., Joseph, G., & Ratha, D. (2009*). Remittances and Natural Disasters: Ex-Post Response and Contribution to Ex-Ante Preparedness.* (Policy Research Working Paper 4972). Washington, DC: World Bank.

Munasinghe, M., Munasinghe, S., Deraniyagala, Y., Perera, S., Jayasinghe, P., Sapukotana, U., Dharmaratna, I. (2007). *Aftermath of the Tsunami.* Colombo, Sri Lanka: Munasinghe Institute of Development.

Rose, A. Z. (2009). *A Framework for Analyzing the Total Economic Impacts of Terrorist Attacks and Natural Disasters.* Published Articles & Papers, Paper 78. Retrieved from http://research.create.usc.edu/published_papers/78

Savage, H., & Paul Harvey, P. (2007). *Remittances during crises Implications for humanitarian Response.* The Humanitarian Policy Group, UK: The Overseas Development Institute.

Skidmore, M. (2001). Risk, natural disasters and household savings in a life cycle model. *Japan and the World Economy*, 1*3,* 15-34.

Suleri, A. Q. & Kevin Savage, K. (2006). *Remittances in crises: a case study from Pakistan.* The Humanitarian Policy Group Background Paper, UK: The Overseas Development Institute.

Swada, Y., Shimizutani, S. (2007). How do people cope with natural disasters? : Evidence from the Great Hanshin-Awaji (Kobe) earthquake in 1995. *Journal of Money, Credit and Banking, 40*(1-2).

World Bank. 2013. *World Development Report 2014: Risk and Opportunity—Managing Risk for Development.* Washington, DC: World Bank. doi: 10.1596/978-0-8213-9903–3

Yang, D. & Choi, H. (2007). Are remittances insurance? Evidence from rainfall shocks in the Philippines*. World Bank Economic Review*, *21*(2), 219-248.

Appendix 1: Components of household income and consumption

Income components	Description	1995, 2006, 2009 and 2012	2002
Paid income	Income from paid employments (wage/salaries, commissions, bonus, arrears)	√	√
Agricultural Income	Income from engage in agricultural activities including value of amount consumed by the household	√	√
Non-agricultural Income	Income from engage in non-agricultural activities including value of amount consumed by the household	√	√
Remittance	Local and foreign remittance	√	√
Transfers	Receipts of government transfer payment, disability and relief payments	√	√
Dividends	Dividends and interests	√	√
Rents and other income	Property rents and other cash receipts	√	√
Adhoc income	Loans taken, sales of assets, withdrawal of savings, income received from welfare societies, repayment of loans given, insurance compensations, lottery and other adhoc gains	√	X

Income components	Description
Food	Value of consumed food (include freely received or home grown) of the main house hold excluding boarders and servants
Non food	Household expenditure on housing fuel and light Personal care Health expenses Transport and communication expenses Education expenses Expenditure in recreation and cultural activities Expenditure on nondurable household goods Household services (laundry, grinding etc.) Clothing textiles and foot wear Durable household goods Non consumption expenses: Savings, payment of Insurance, debt, income tax, contributions to trade unions, thrift societies and social security payments (provident fund), expenses on social activities, donations, loans given.
Servants	Expenses on servants food and non-food consumption

Appendix 2: Damage caused by Tsunami

District	Deaths	Displaced population	Population that become homeless	Public infrastructure damage (Rs. Million)
Jaffana	2640	39607	20734	1716.4
Mulativu	3000	22657	22831	2166.1
Trincomalee	1078	81643	36326	3446
Batticaloa	2840	61912	70282	3208.4
Ampara	10436	75172	67707	3959.2
Hambantota	4500	17723	8955	1296.5
Matara	1342	13206	28860	2216.9
Galle	4214	128077	53440	4289.9
Kaluthara	256	27713	24855	1009.4
Colombo	79	31239	24457	235.1
Gampaha	6	1449	4401	348.1
Puttlam	4	66	228	16.9
Kilinochchi	0	1603	1186	232.3
Mannar	0	0	0	11

Source: Department of census and Statistics (2006)