Sri Lankan Households a Decade after the Indian Ocean Tsunami

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ABSTRACT

This study estimates the causal effect of the Indian Ocean tsunami in Sri Lanka on household income and consumption eight years after the event, using a Difference in Difference method. Deviating from the common observation on short-term impacts, these results are suggestive of a potential for some long-lasting and more successful recovery scenarios. We observe a strong association between area-wide tsunami disaster shock and increases in household income and consumption in the long-term. Still, Sri Lanka received a very large amount of external assistance post-tsunami, much larger than is typical for disaster events and one which may not be replicable. These findings demonstrate the possibility of a successful recovery from a catastrophic disaster that generated growth and benefited households. This is a novel understanding of a catastrophic disaster happening in a relatively poor country that is on a rapid growth path.

KEYWORDS

Sri Lanka, Tsunami, disaster, household survey, long-run impact

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

[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).

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 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.

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 in the seven affected districts is examined in quasi-experimental (diff-in-diff) setting using cross sectional household data. Since the intensity of damages varies across districts, the analysis also sheds light on the spatial dynamics of the disaster recovery.

RELATED LITERATURE ON DISASTER LOSSES

The large literature on the losses associated with disasters examines consequences at both the micro- and macro-level. Theoretical models on one hand (Dacy and Kunreuther, 1969; Okuyama, 2003) suggest that the disasters on aggregate output are neutral in the long term. In contrast, the 'creative destruction' hypothesis (Benson and Clay, 2004; Skidmore and Toya, 2002; Albala-Bertrand, 1993) posits that one should observe positive economic growth when destroyed capital is replaced with the most recent technological frontier or it shifts in investment towards human capital (Hallegatte and Dumas, 2009). 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) and 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 savings 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

[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).

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 on well-being: reduced height and body mass index for children experiencing these events (Alderman, Haddinot and Kinsey, 2006; Haddinot, 2006), a strong negative correlation between disasters and secondary school enrolment (Cuaresma (2009), a relative deficit in educational and labour outcomes for those exposed to massive earthquakes (Bhalotra, Sanhueza and Wu, 2011; Cruso and Miller (2015).

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, 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 household's reactions to disasters (Deshingkar and Aheeyarse 2006; Harvey and Group, 2007; Mohapatra et al., 2009; Savage et al., 2007) to recover earlier from catastrophic disasters like earthquakes (Suleri and Savage, 2006) and typhoons (Gröger and Zylberberg, 2015). 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.

Given the localized impacts of tsunami along to coastal strip, and the availability of several waves of post-event household survey data that include geographic information, we are able to describe the dynamics experienced by tsunami-affected households in the decade following the event itself. Our main contribution in this paper is the focus on the long-term impacts of the event, while most of the previous literature cited above focuses on very short-term impacts.

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).

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 Reconstruction and Development Agency (RADA) established in November 2005. 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 funding. The government of Sri Lanka initially estimated 2.0 billion including an ambitious build back long term reconstruction program (GOSL, 2005). Almost 1.4 billion were spent on reconstruction 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] 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.

EMPIRICAL ANALYSIS OF HOUSEHOLD SURVEY

This study isolates the causal effect of the 2004 tsunami on household income and consumption 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 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 Hosehold 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 (model 2). 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 is estimated for a different treatment group excluding the two richest districts (Colombo and Gampaha) and the other for a treatment group including only the two richest districts (Colombo, Gampaha).

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

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

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.

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.

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 (i) number of affected GN divisions divided by the total number of GN divisions in respective District, (ii) population in destroyed and damaged houses in each district divided by the total population in each affected district, (iii) population in the affected DS divisions in each district divided by the total population in each respective district, (iv) total deaths in each district divided by district population and (v) displaced population in each district divided by the district population.

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

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

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.

Variable	Mean	Std. Dev.	Min	Max
Sex (Household head)	.79	.42	0	1
Age (Household head)	51	14.04	10	99
Education(Yr) (HH head)	7	2.94	0	18
Ethnic grp. Sinhalese	.85	.35	0	1
Ethnic group-Tamil	.14	.35	0	1
Household size	4	1.88	1	20
Household in rural sector	.81	.39	0	1
Household in urban sector	.13	.34	0	1
Household in estate sector(Dummy)	.05	.22	0	1
Household - After Tsunami	.64	.48	0	1
Household affected by Tsunami	.51	.50	0	1
Affected Household observed after Tsunami	.33	.47	0	1
Income (Rs./month)	8536.23	12497	-3595	98732
Consumption (Rs./month)	11692.86	10584	297	87436

Table 1. Summary statistics

Income

Table 2 presents the results for household income using our preferred specification as it includes district clustered standard errors. 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. Table 2, Column (i) (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. 7046 (47 US$), slightly reduced in the year 2009 (Rs. 5870, 39.14 US$) and increased significantly in the year 2012 by Rs. 15142 (100 US$). For further verification of whether observed treatment effect could be due to the treatment district's specific time trends rather than the treatment itself, we include a linear district-specific time trend in column (ii); The inclusion of these time trends does not have much impact on the estimated coefficients of interest.

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 indicate 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. Figure 2 shows the impact across affected regions.

The results of the same model using five treatment indicaters (equation 3) are presented in column (iii) to column (vi). As in column (ii) of table 3, when estimated for the treatment group of the most-affected regions (column v), reveals a much more moderate income increase shortly after the tsunami - Rs. 2678 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. Again, this suggests the role that assistance played in recovery, with less affected districts benefiting the most.

Column (iii) 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 (vi), where the model estimated focuses on the ATE for the richest two regions. The identified ATE is 3-4 times as large for the richest as for the poorest affected regions (column iii).

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 ii – our preferred specification including district time trends. In paid and non-agricultural income sources, the identified ATE for the three post-tsunami years is positive, though some of the estimated coefficients are 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. 6934 (53 USD), in 2009 by Rs. 7242 (55.7 USD) and 2012 by Rs. 10675 (82 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 higher 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.[5] We note 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

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

be quite intuitive. When examining districts separately, we find that Colombo (CMB) and Gampaha (GMP) have significantly higher incomes; while most other districts have lower income post-tsunami.

Independent Variables	**(i) Average effct across all districts Robust SE**	**(ii) District Clustered Robust SE**	**(iii) Exclude Richest districts**	**(iV) High intensity districts**	**(v) Low intensity districts**	**(vi) Richest Districts**
Treatment*2006	7048 (2428) ***	7022 (2898) ***	2678 (1568) *	2626 (1280) **	6574 (3551) *	11763 (1845) ***
Treatment*2009	5870 (1681) ***	5787 (2474) ***	2864 (1246) **	2832 (840) ***	5572 (2822) **	9257 (1098) ***
Treatment*2012	15142 (3992) ***	15066 (4802) ***	8096 (3189) ***	8536 (1812) ***	13406 (6915) *	22894 (2932) ***
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Household covariates	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	Yes	Yes	Yes	Yes
District time trend	No	Linesr	linear	linear	Linear	linear
constant	-600 (1050) *	1497 (568) ***	3510 (1212) ***	1008 (1811)	-629 (1205)	-546 (1101)
R-squared	0.49	0.52				
Observations	84393	84393	65996	55974	52051	58871

Table 2. Impact of tsunami on household income

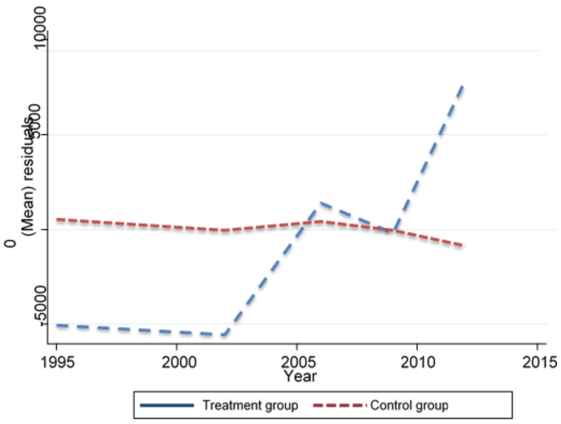

Figure 1. Noirmalized income

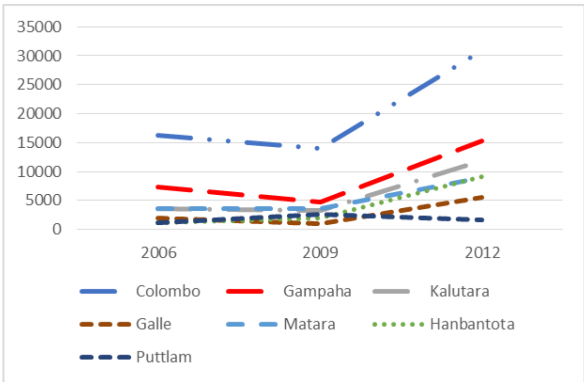

Figure 2. Income effect across districts

Income sources	Paid income	Agricultural Income	Non-agricultural Income	Remittance	Transfers	Dividends	Rents and other income
Treatment* 2006	994 (1282)	-1030 (574) *	6934 (2777) ***	42 (133)	144 (110)	-18 (26)	-155 (243)
Treatment* 2009	172 (1214)	-1456 (657) **	7242 (2917) ***	59 (126)	23 (197)	-9 (33)	-44 (355)
Treatment* 2012	4243 (2181) **	-1544 (660) **	10675 (4024) **	839 (256) ***	789 (205) ***	67 (43)	-179 (360)
Constant	1122 (880)	-43 (203)	1205 (567) **	-286 (116) ***	-272 (154)*	-23 (20)	-69 (129)
R-squared	0.35	0.15	0.24	0.06	0.08	0.01	0.03

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

Consumption

Tables 4 includes 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 (i) of includes the household covariates and the district fixed-effects, and is estimated with district clustered standard errors. In column (i), 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 iv 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 iv 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 iii and vi 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 (figure 4), 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 4 column vi, viii). When distinguishing between food and non-food expenditures, we find that, food consumption actually increased in the affected districts as a consequence of the tsunami, while non-food consumption increased marginally in year 2012.

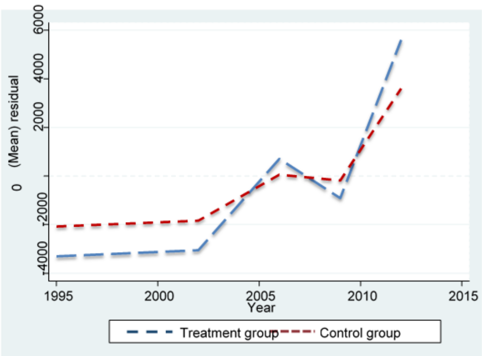

Figure 3. Normalized Consumption

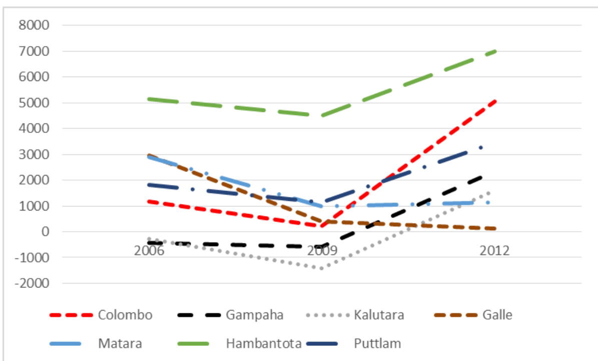

Figure 4. Consumption effct across districts

Independent Variables	**(i) Average effect Of all districts**	**(ii) Average effect Of all districts**	**(iii) Exclude richest districts**	**(iv) High intensity districts**	**(v) Low intensity districts**	**(vi) Richest Districts**	**(vii) Food cons.**	**(viii) Non-food cons.**
Treatment*2006	1235 (500) ***	1343 (735) *	1621 (466)***	2014 (421) ***	426 (479)	886 (702)	597 (284) **	789 (622)
Treatment*2009	214 (279)	333 (500)	-55 (331)	-424 (330)	291 (156) *	510 (251) **	711 (382) *	-318 (375)
Treatment*2012	2824 (1096) ***	2981 (925) ***	1252 (1281)	-449 (891)	3335 (752) ***	4507 (745) ***	1459 (525) ***	1546 (776) ***
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Cov.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District time trend	No	No	linear	linear	linear	Linear	linear	linear
constant	-342 (1062) ***	2062 (1122)*	3291 (1209)***	413 (1043)	973 (777)	2273 (1496)	3771 (98) ***	-1829 (1154)
R-squared	0.29	0.29	0.25	0.24	0.27	0.30	0.27	0.23
Observations	84393	84393	65996	55974	52051	58871	84393	84393

Table 4: Impact of tsunami on Household consumption

CONCLUSION

Few research projects attempted 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 very little aggregate effects at the national level and more substantial adverse local long-term effects. Yet, little is really known about the impacts at the micro/household level in the longer term. Here, we estimated the effect of the Indian Ocean tsunami in Sri Lanka on household income and consumption eight years after the event, using a difference in difference 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. More importantly, recovery we observe gives a record of the disaster effect on directly affected households, spillovers to unaffected neighboring households and captures ex-post reactions to the disaster and household risk preparedness pre and post disaster.

We note that 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 we identified, can be associated not with ‘creative destruction’, but purely due to the infusion of atypically massive amounts of external resources for rebuilding. Only an accounting for the amount of assistance received, per district, could possibly start to allow us to differentiate between these two hypotheses; regrettably, such accounting in the analysis is impossible due to lack of aid data.

Our findings suggest a more nuanced picture with respect to household consumption impacts. Concurrently with the increases in income, we observe an increase of food consumption expenditure and only find a marginal increase in non-food consumption. The increase in food consumption, however, is much smaller than the increase in income. As household expenditures on durable assets are not available in all survey waves, we are unable to evaluate the translation of household income to such assets.

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