World Development 105 (2018) 217–230

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Impact of natural disasters on income inequality in Sri Lanka

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ARTICLE INFO

Article history:
Accepted 1 January 2018

JEL classification:
Q54
O11
O15

Keywords:
Natural disasters
Economic impact
Income inequality

ABSTRACT

We explore the relationship between natural disasters and income inequality in Sri Lanka as the first study of this nature for the country. The analysis uses a unique panel data set constructed for the purpose of this paper. It contains district inequality measures based on household income reported in six waves of the Household Income and Expenditure Survey of Sri Lanka during the period between 1990 and 2013, data on disaster affected population and other economic and social indicators. Employing a panel fixed effects estimator, we find that contemporaneous natural disasters and their immediate lags significantly and substantially decrease inequality in per adult equivalent household income as measured by the Theil index. Findings are robust across various inequality metrics, sub-samples and alternative estimators such as Ordinary Least Squares and System GMM. However, natural disasters do not affect household expenditure inequality. Either households behave as if they have a permanent income or all households reduce their expenditure proportionately irrespective of their income level in responding to natural disasters. Natural disasters decrease non-seasonal agricultural and non-agricultural income inequality but increase seasonal agricultural income inequality. Income of richer households is mainly derived from non-agricultural sources such as manufacturing and business activities and non-seasonal agricultural activities. Poorer households have a higher share of agricultural income.

1. Introduction

Natural disasters disproportionally affect the poor. It is therefore often assumed that natural disasters increase income inequality. However, as Karim and Noy (2016) point out, there is little research on the impact of natural disasters on income inequality. This paper contributes with a study of Sri Lanka.

We study the impact of natural disasters on income inequality in Sri Lanka at district level, as the first study of this nature. We find that natural disasters decrease income inequality among Sri Lankan households. These findings may be somewhat surprising on the face of it as one would expect natural disasters to exacerbate income inequality. However, at subsistence level, people possess little that can be lost to a natural disaster. Losses for the wealthier groups would be disproportionately greater due to natural disasters. People on a monthly wage would not see their income affected by a disaster, but small business owners would. Unskilled day labourers may find new opportunities in the reconstruction effort.

Investigating the impact of Cyclone Aila in Sundarbans region in Bangladesh in 2009, Abdullah, Zander, Myers, Stacey, and Garnett (2016) establish that income inequality decreased after the cyclone. Another very recent paper by Feng, Lu, Nolen, and Wang (2016) show that household income fell by 14% due to 2008 Sichuan earthquake in China, however, income inequality did not change.

Our findings are in line with the results of the aforesaid two studies on Bangladesh and China (Abdullah et al. (2016), Feng et al. (2016)). Our data allow us to decompose income sources, so that we better understand the mechanisms.

The paper proceeds as follows. Section 2 presents a background discussion with related existing literature. Section 3 describes data and empirical strategy. Results are discussed in Section 4 followed by Section 5 which contains robustness checks. Section 6 sets out

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https://doi.org/10.1016/j.worlddev.2018.01.001
0305-750X/

concluding remarks with some policy implications and also recognises the limitations of the study.

2. Background discussion

In the aftermath of a natural catastrophe, it is essential that affected agents should have access to timely and sufficient finances to ensure a smooth and speedy recovery (Keerthiratne & Tol, 2017). Flow of foreign aid that follows a natural disaster plays a key role in the economic recovery process. Enterprises would recover fast when they are provided with additional capital after a natural disaster. Using a randomised experiment where randomly selected enterprises in Sri Lanka were given cash grants after the tsunami, De Mel, McKenzie, and Woodruff (2012) present evidence for this.

Wealthy individuals are in a better position to meet the financial requirement through self-financing as they can use their savings for reconstruction, they are more likely to have bought insurance to cover any losses, and they have better access to loans and credit. Not only that, the rich are often better prepared for natural disasters as they can financially afford to have precautionary solutions to avoid or mitigate disaster damages. Further, the poor are more likely to have irregular income, so that every disruption, either due to the disaster directly or dealing with the aftermath, means a loss in income. As such, even within the same country, natural disasters would differently affect rich and poor individuals. Natural disasters may thus negatively affect the level of income of the poor leading to a widened income inequality in society.

Furthermore, disaster affected territories generally suffer economic damages by way of human and physical capital losses which usually cause declines in average incomes. Accordingly, this may lead to spatial disparities in average incomes ultimately increasing income inequality among individuals within the same economy.

However, microfinance can act as a recovery tool for poor households in the aftermath of severe natural disasters. Using Sri Lanka after the 2004 tsunami as a case study, Becchetti and Castriota (2011) show that real income and working hours were increased as a result of loans from micro finance institutions.

As Karim and Noy (2016, p. 4) highlight, it is apparent from the existing literature that "poorer households are more vulnerable and will bear the direct damages of disasters disproportionally at higher levels and as higher shares of their household's income" compared to rich households (Datt & Hoogeveen, 2003; Kim, 2012; Masozera, Bailey, & Kerchner, 2007; Morris et al., 2002; Rodríguez-Oreggia, 2010; Tesliuc & Lindert, 2002; Toya & Skidmore, 2007).

When a disaster strikes, the magnitude of its impact on an economy depends on characteristics of disaster itself and the prevailing conditions and socio-economic status of the affected territory as a whole. It appears that as a result of a similar natural disaster event more vulnerable poor countries suffer to a greater extent as opposed to their well-prepared wealthy counterparts. Quoting the World Bank, McDermott, Barry, and Tol (2014, p. 751) highlight that 97% of deaths related to natural disasters occur in developing countries and poor countries experience extremely high economic losses as a share of gross national product than rich countries due to natural disasters.

Whilst arguing that natural disasters cause human and economic losses irrespective of the level of economic development countries have achieved, Yamamura (2015) employs panel data for 86 countries covering the period from 1970 to 2004 to examine how the occurrence of natural disasters has affected the income inequality, as measured by Gini coefficient. He finds that natural disasters increase income inequality in the short run, however, this is not observable in the long run.

As Karim and Noy (2016, p. 4) suggest "the direct impact of disasters on the poor (in magnitude, and relative to the rich) cannot be answered" fully by merely "examining the cross-country distribution of costs and economic activity. . .the evidence on the distribution of the direct impact of a disaster within a country on households in various income levels is less well understood" as it clearly depends on country characteristics. As such, country-level research is warranted in this field.

Using the Vietnam Household Living Standard Survey in 2008, Bui, Dungey, Nguyen, and Pham (2014) find that natural disasters increased income inequality among households in Vietnam in 2008. When natural disasters occur, households can suffer large losses in assets and income. However, poor may be more vulnerable to loss of income due to their inability to engage in work and the unavoidable sale of income deriving capital assets as a coping strategy. If poorer households are less prepared for disasters; the poor live in disaster prone areas and homes that are more likely to be damaged; and receive earnings mainly from sectors which are more likely to face downturn (e.g., weather dependent traditional agriculture), poor would bear higher income losses and natural disasters could cause greater income inequality.

However Abdullah et al. (2016) and Feng et al. (2016) found results in contrary to the above as mentioned in the Introduction. In other words, the impact of natural disasters on income inequality is ambiguous.

3. Empirical analysis

3.1. Data

Natural disaster data are from the Disaster Management Centre of Sri Lanka, which maintains disaster related data in collaboration with 'DesInventar', the Disaster Information Management System of UNISDR, United Nations Office for Disaster Risk Reduction. Income data and other social and economic indicators are obtained from the Household Income and Expenditure Survey (HIES) series conducted by the Department of Census and Statistics of Sri Lanka from 1990 to 2013. There are six waves, i.e. 1990/91, 1995/96, 2002, 2006/07, 2009/10 and 2012/13 where the data are representative at district level. Note that these are not panel data. The only wave which covers the entire country is the 2012/13 survey. Due to the ongoing civil war at that time, some districts of Northern and Eastern provinces were not covered in earlier waves. Mid-year district population data are taken from the Registrar General's Department of Sri Lanka and the study uses the Consumer Price Index published by the Central Bank of Sri Lanka.

Extracting the data reported in the official website of Disaster Management Centre, we construct a district-wise annual disaster database for Sri Lanka from 1985 to 2013. It contains the number of people affected due to cyclones, droughts, epidemics, floods, gales, heavy rains, landslides, land subsidence, plagues, storms, strong winds, surges, tornados, and tsunami in each district, yearly. According to the database, around 27 million people were affected from natural disasters in Sri Lanka during the period from 1985 to 2013. Of them, 47% and 45% were affected by droughts and floods, respectively. Extreme wind events were responsible for 6% of the population affected whilst 2% were affected due to epidemics. Following Noy (2009), we normalise the number affected by disasters with lagged population. Thus, disasters are measured as the percentage of population affected due to all natural disasters in each district during a calendar year.

Potential alternative choices for disaster measures would have been the number of total deaths or mortality, morbidity or the total monetary damage caused by a disaster. Keerthiratne and Tol (2017) have paid special attention to these alternative choices for disaster outcomes. They state "the economic data may be gathered by the individuals who attend the affected area primarily with the intention of providing medical care and physical aid. Therefore, they may lack the expertise to estimate of the economic loss. Of the numbers of people killed and affected, the preferred variable is the number of people affected. In some instances, even a severe disaster may not kill as shown by Gassebner, Keck, and Teh (2010), Cavallo and Noy (2011) and Klomp (2014). Hence, in this study, the number of people affected by natural disasters in a country year is chosen as the variable of interest. Accordingly, our analysis is limited to disasters where there are reported affected population. Following Noy (2009), the disaster variable is normalized as the percentage of population affected". Owing to similar reasons, we preferred the same disaster measure subject to aforementioned limitations. Moreover, this measure appeared to be the most complete and reliable one available in the disaster database.

To explore the impact of natural disasters on income inequality at district level in Sri Lanka, we compute the monthly income of each household in the survey year based on survey data of HIES series. In the calculations, we take into consideration all monetary and non-monetary income derived from all sources. Free State services, such as education and health, the value of which cannot be ascertained easily and exactly, were not included in the income. Accordingly, household income consists of the followings components (Department of Census & Statistics, 2015).

a) Employment income – wages-salaries, allowances (tips, commissions, overtime), bonus and arrears
b) Seasonal agricultural income – paddy, chillies, onions, vegetables, cereals, yams, tobacco
c) Non-seasonal agricultural income – tea, rubber, coconut, coffee, pepper, betel, banana, fruits, meat, fish, egg, milk, other food, horticulture
d) Non-agricultural income – mining and quarrying, manufacturing, construction, trade, transport, guest house, restaurants, bars, hotels, etc.
e) Cash receipts – such as pensions, disability / relief payments, dividends, rents, interest amounts received from various types of savings, educational grants and scholarships, school food program, current remittances and local and foreign transfers, other income
f) Windfall income – income by chance or *ad hoc* gains such as compensations, lottery wins, loans, sale of assets such as land, house and jewellery, withdrawals from savings and bank deposits, gratuity, provident fund, income received from births, deaths and marriages, receipts from welfare society, *seettu* (an informal savings scheme among households), repayments of loans given, health and medical aid, insurance, foods and other commendations, disaster relief assistance, etc.
g) Non-monetary income
   i. Food in kind (mostly the estimated values of the household consumed items such as home-grown fruits and vegetables)
   ii. Non-food in kind (includes estimated rental values of owner occupied housing units)

Household monthly income is calculated by aggregating monthly earnings received from all the components and then it is equivalised to take account of differences in household size and composition so that it becomes a representative income. To adjust incomes on the basis of household size and composition, all incomes are expressed as the amount that an adult would require to enjoy the same standard of living. We employ the widely used Organisation for Economic Co-operation and Development (OECD) modified equivalence scale for this purpose. This scale, first proposed by Hagenaars, De Vos, and Asghar Zaidi (1994), assigns a value of 1 to the household head, of 0.5 to each additional adult member and of 0.3 to each child. A caveat is that OECD modified scale takes into account only the age and number of members in a household even though there may be other characteristics which may vary from household to household such as disability or health status of household members that affect the needs and capacities of such households.

Adjusted household monthly income per adult equivalent after accounting for sample weights is used to calculate mean and median household incomes and inequality measures such as Theil index (Theil, 1967), Gini coefficient (Gini, 1936), inter quartile range and inter quintile range for average income for each district for each survey year. Income measures are converted to real terms using Colombo Consumers' Price Index (annual average, base year 2006) for comparison across survey years.

From the HIES 2006/07 onwards, 7 new sections have been introduced to the HIES series to collect almost all other household information that helps to understand the living standards of the households. These new areas are school education, health information, inventory of durable goods, access to infrastructure facilities, household debts and borrowings, information on housing, sanitary and disasters, and land and agriculture holdings (Department of Census & Statistics, 2015, p. 1).

Based on the above, we construct a panel dataset which contains data on household incomes and expenditures, income and expenditure inequalities, natural disasters, etc. for 25 administrative districts in Sri Lanka for six survey time periods. This is an unbalanced panel as the number of districts covered varies between 17 and 25. The only wave which covers the entire country is the latest 2012/13 survey. Due to the ongoing civil war at that time some districts of Northern and Eastern provinces were not covered in other waves.

Any inequality measure should satisfy the four main axioms of inequality. They are anonymity (what matters is how the income is distributed in the economy irrespective of who the individuals are), scale independence (inequality does not depend on the magnitude of the aggregate income), population independence (it is independent of the level of population) and Pigou-Dalton transfer principle (when some income is transferred from rich to the poor, inequality should not increase). Theil index was chosen as the major inequality measure for this study considering its decomposability in addition to the above properties. We use other alternative inequality metrics such as Gini coefficient and inter quartile range to check the validity of our findings.

Summary statistics for the variables used in the analysis are provided in Table 1. On average, disasters affect 5% of the population in a district per annum in Sri Lanka and the maximum percentage of population affected by natural disasters in a district can be as high as 118% (due to multiple disasters in a year). Fig. 1 demonstrates the variation of mean percentage of population affected due to natural disasters across districts in Sri Lanka.

District-wise income inequality measured by Theil index is around 0.44 whilst Gini co-efficient is around 0.43. Per adult equivalent real mean household income is Rs. 8891 (in constant 2006 rupees). It is also observed that the income of the richest quintile is more than 10 folds larger compared to the poorest quintile. Average household size is around 4 and about 15% of the households are poor. Around 2% of housing units are basic with no rooms. Around 38% of households do not possess vehicles or electric equipment. Meanwhile, around 13% of households do not have access to safe drinking water and around 4% of households do not have an exclusive toilet.

Table 2 shows how income and inequality measures differ by district. We observe a substantial variation of inequality among districts in Sri Lanka. Kurunegala District records the highest

Table 1
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Theil	117	0.4396	0.3027	0.1675	2.4802
Gini	117	0.4276	0.0614	0.2880	0.7168
IQ^4R (Inter Quartile Range in Rs.)	117	5,698	2,108	2,457	12,458
IQ^5R (Inter Quintile Range, Avg. Inc. in Rs.)	117	20,688	10,433	8,383	74,676
Mean Household Income (Rs.)	117	8,891	3,388	4,404	20,580
Median Household Income (Rs.)	117	6,228	1,926	3,302	13,409
Q1 Average Income (Rs.)	117	2,075	1,463	−9,823	5,627
Q2 Average Income (Rs.)	117	4,490	1,386	2,223	9,809
Q3 Average Income (Rs.)	117	6,264	1,945	3,326	13,534
Q4 Average Income (Rs.)	117	8,941	2,951	4,552	19,437
Q5 Average Income (Rs.)	117	22,763	10,929	10,109	77,315
HCI (Head Count Index)	117	19.00	11.56	1.40	56.20
% of Poor Households	100	15.48	11.05	1.10	42.20
Household Size	117	4.23	0.38	3.68	5.13
% of Households without Electrical Items	66	38.17	15.37	4.70	90.60
% of Households without Vehicles	66	38.07	22.20	10.50	90.80
% of Households with No Rooms	65	2.20	1.87	0	9.00
% of Households with No Safe Drinking Water	66	13.17	10.93	0.50	48.60
% of Households with No Toilet	62	4.31	5.02	0.10	24.40
Disaster (% of Population Affected)	150	4.7368	13.4126	0	117.6589
Disaster_lag1	150	8.5613	22.1317	0	174.3878
Disaster_lag2	150	11.7633	23.4198	0	128.5260
Disaster_lag3	150	4.0579	8.0361	0	56.1630
Disaster_lag4	149	4.8619	10.9804	0	62.4662
Disaster_lag5	149	10.7272	24.9794	0	174.3878
Biological (% of Population Affected)	150	0.1079	0.2629	0	3.1072
Climatic (% of Population Affected)	150	2.2285	11.4782	0	117.5446
Geophysical (% of Population Affected))	150	0.0137	0.1240	0	1.4415
Hydrological (% of Population Affected)	150	2.1009	6.5334	0	52.6214
Meteorological (% of Population Affected)	150	0.2859	2.9010	0	35.5536

Notes: Q1–Q5 are the income quintiles. IQ^4R is the inter quartile range or the income difference between the 75th percentile and the 25th percentile. IQ^5R is the difference between the average incomes of the fifth and first quintiles.

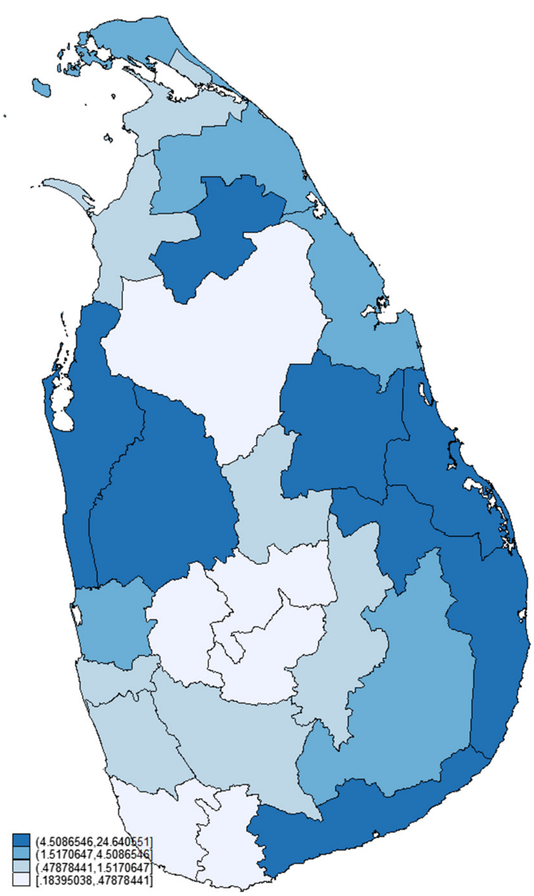

Fig. 1. Variation of mean percentage of population affected due to natural disasters.

inequality whilst Mannar District records lowest inequality as measured by both Theil index and Gini coefficient. Fig. 2 and Fig. 3 demonstrate the variation of mean inequality measured by Theil index across districts in Sri Lanka.

Fig 4 presents within district variation of inequality as measured by Theil index over time. No such variation is presented for Jaffna, Kilinochchi and Mannar Districts as these districts were covered only in the last survey wave, i.e., 2012/13. We can observe a considerable variation of inequality over time for almost all the districts and this is the variation we exploit in this paper.

Fig. 5 depicts the relationship between current natural disaster affected population (%) and income inequality measured by Theil index after controlling for disaster lags, time invariant district fixed effects and time fixed effects. There appears to be a significant negative correlation between disasters and income inequality suggesting a possible reduction of income inequality by natural disasters.

3.2. Empirical model

We employ a panel regression estimator with district and time fixed effects as the main estimation strategy in our analysis. Fixed effects estimator is chosen since district and time fixed effects control for time-invariant spatial heterogeneity among districts and time-variant shocks that simultaneously affect all the districts, respectively. As such, this approach reduces any potential endogeneity issue.

The panel regression equation of the baseline model is as follows;

$$Inequality_{it} = \alpha_i + \beta_t + \gamma Dis_{it} + \Gamma Dis_{i,t-n} + \varepsilon_{it} \quad (1)$$

where income inequality as measured by Theil index in district i in Sri Lanka for survey time t is the dependent variable. *Dis* is our variable of interest, disaster impact measured as the percentage of

Table 2
Average income and inequality measures by districts.

District	Mean Income	Median Income	Theil	Gini	IQ^4R	IQ^5R
Ampara	8483	6358	0.3788	0.4262	5669	18,419
Anuradhapura	8650	6472	0.3801	0.4003	5440	18,231
Badulla	7692	5363	0.3807	0.4284	4898	17,422
Batticaloa	7856	5987	0.3212	0.4077	5461	16,488
Colombo	14,774	9558	0.4891	0.4654	9719	36,015
Galle	8787	6153	0.4403	0.4243	5386	19,851
Gampaha	11,629	8074	0.4414	0.4248	7443	26,731
Hambantota	8363	6146	0.3373	0.4087	5628	18,087
Jaffna	7021	5277	0.3672	0.4168	4756	16,921
Kalutara	9513	6840	0.3356	0.4095	6389	20,305
Kandy	8636	5803	0.4732	0.4527	5656	20,643
Kegalle	7234	5500	0.3080	0.3921	4765	15,021
Kilinochchi	7357	6017	0.4853	0.4716	5932	21,660
Kurunegala	10,251	5909	0.8070	0.4873	5609	28,601
Mannar	7109	6352	0.1784	0.3206	4889	11,974
Matale	6705	4930	0.3462	0.4215	5,242	17,141
Matara	7436	5477	0.3195	0.4060	5,583	17,229
Monaragala	8035	5880	0.4657	0.4456	4,757	19,152
Mullaitivu	6585	5436	0.3091	0.4145	4,824	13,861
Nuwara Eliya	8076	5496	0.6049	0.4153	3,911	18,537
Polonnaruwa	9457	6313	0.5477	0.4245	5,719	22,674
Puttalam	8809	6209	0.4577	0.4320	5,385	20,411
Ratnapura	8392	5387	0.5605	0.4614	4,784	21,264
Trincomalee	8617	6423	0.3660	0.4079	5,786	18,175
Vavuniya	12,130	8670	0.3629	0.4365	9,350	27,098

Notes: IQ^4R is the inter quartile range or the income difference between the 75th percentile and the 25th percentile. IQ^5R is the difference between the average incomes of the fifth and first quintiles. Mean income, median income, IQ^4R and IQ^5R are in constant 2006 Rs.

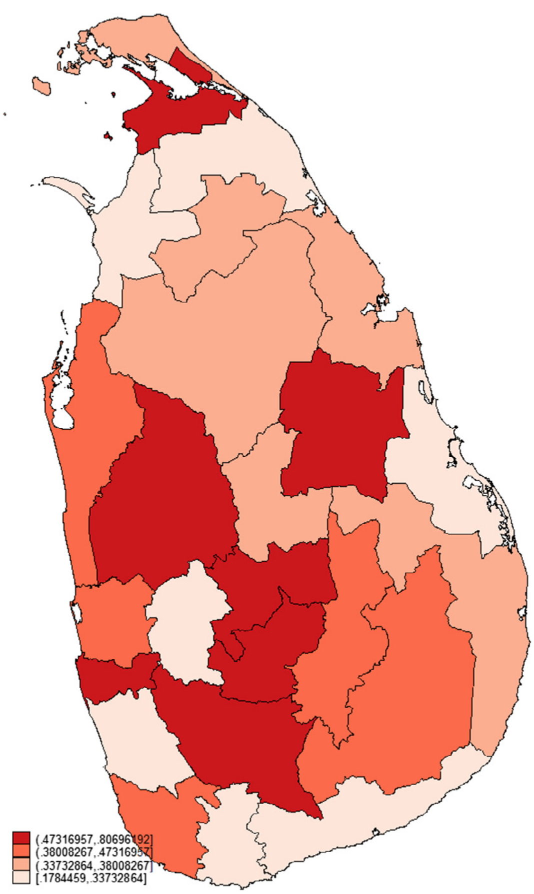

Fig. 2. Variation of mean inequality measured by Theil index across districts.

population affected due to all natural disasters occurred during the survey year in each district. We also include lagged disasters in the regression, as the effects of a natural disasters may last for a long time. Given the data availability, for each survey time five disaster lags are included in the regression in addition to the current disaster variable. Terms α_i and β_t are the district and time fixed effects included in the model, respectively. The final term ε_{it} in the equation is the error term. Errors are clustered at district level.

We check against omitted variable bias by adding more control variables, such as median household income, headcount index, share of poor households and other indicators which reflect social and economic status of households. In addition to the Theil index, we employ other alternative inequality measures such as the Gini coefficient, inter quartile range and inter quintile range of average income as the dependent variable. We rerun regressions excluding the extreme survey waves, i.e., 2006/07 which was after 2004 tsunami and 2009/10 survey which was after the ending of war/terrorism, to ensure that results are not driven by these extreme waves.

Apart from the panel fixed effect estimator we use alternative estimators such as ordinary least squares (OLS) and System GMM to support our findings; see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), Roodman (2009a) and Roodman (2009b). Once we are convinced that natural disasters affect income inequality, we explore how natural disasters affect level of income itself, particularly in different quintiles. As it is evident that income of all quintiles is reduced in the presence of disasters, we decompose inequality measured by Theil index into income components. We compare results with the differences in income composition of poor and rich quintiles as this exercise explains findings.

As we are using the household income and expenditure survey data, we investigate whether there is any relationship between household expenditure inequality and natural disasters. We expand our analysis to disaster subgroups and repeat our analyses excluding biological disasters as the mechanisms are so different. Finally, we repeat our analysis without meteorological disasters since they appear to increase income inequality as the relative loss due to such disasters decreases with income.

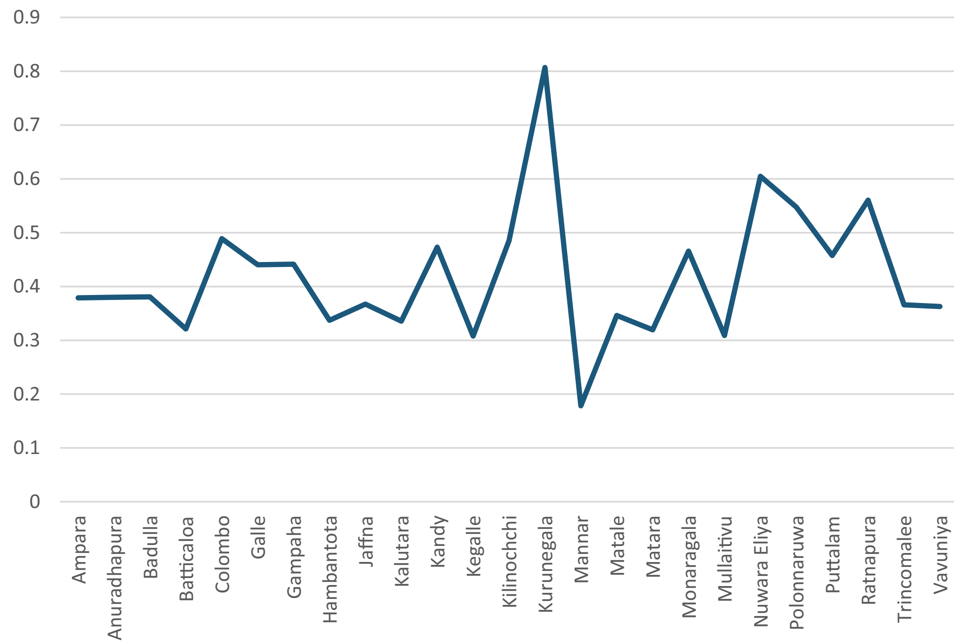

Fig. 3. Variation of mean inequality measured by Theil index across districts, graphical representation.

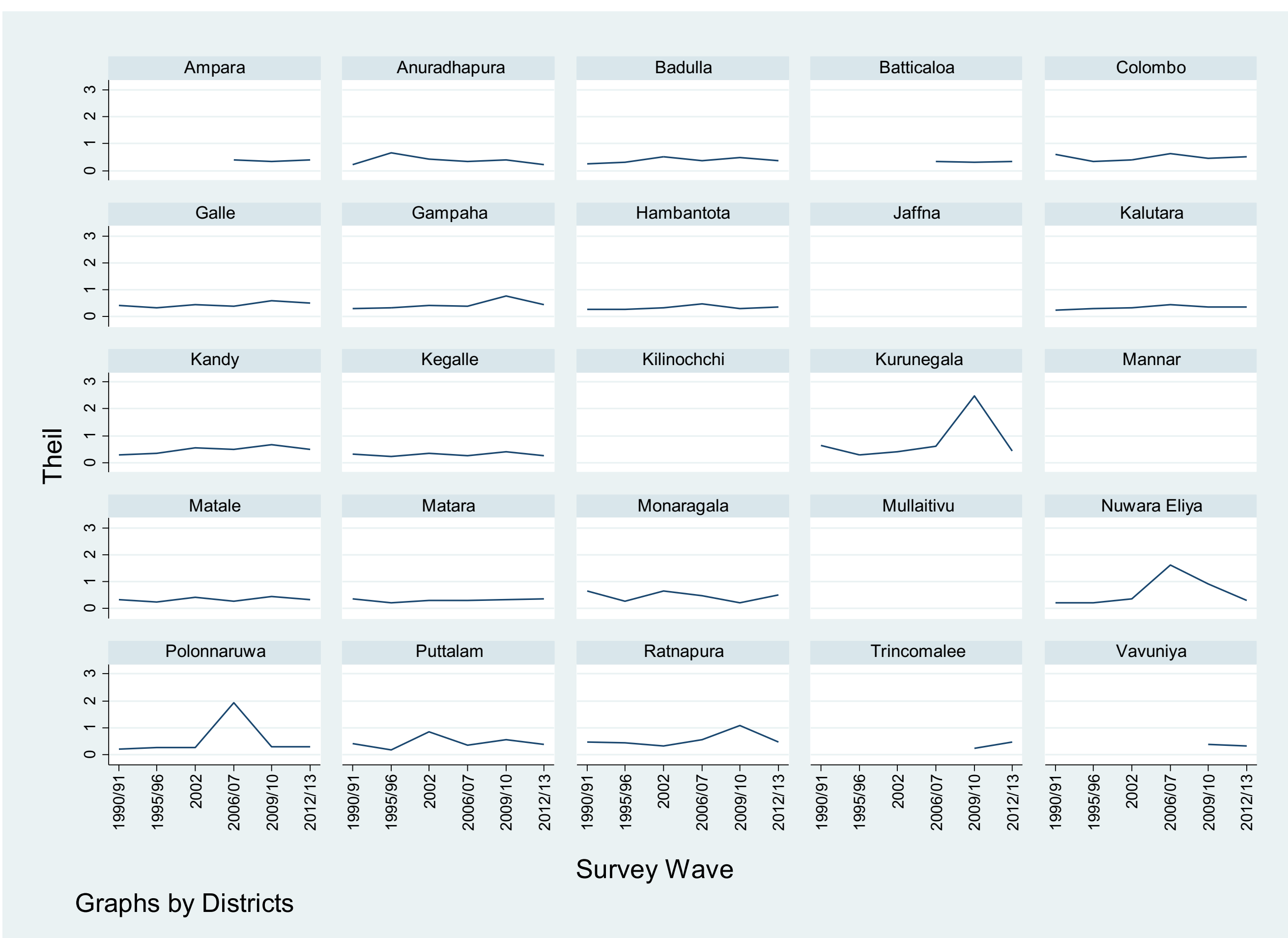

Fig. 4. Variation of inequality measured by Theil index by districts over time.

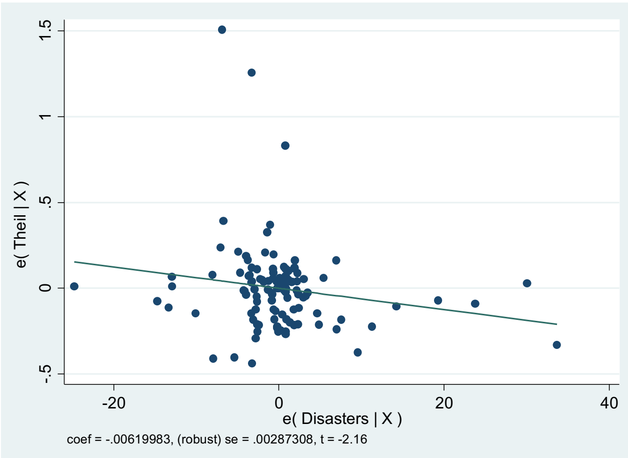

Fig. 5. Association between Theil index and natural disasters.
Notes: This is an added-variable plot, partial regression leverage plot, or adjusted partial residual plot, obtained using avplot command in Stata/IC 14.1. The command regresses the number of people affected by disasters and the Theil index of income inequality on disaster lags, district and time fixed effects, and plots the residuals of both regressions against each other. Having removed the impact of confounders, the graph can be interpreted as a scatter diagram would in a simple regression.

4. Results

4.1. Base model

Results of the baseline model are given in Column 1 of Table 3. We find statistically significant negative impact of natural disasters that occurred in the same year, two years and three years prior to the survey on income inequality measured by Theil index. An increase of current disaster affected population by one percentage point would reduce income inequality measured by Theil index by 0.0062 points, ceteris paribus.

We provide a hypothetical illustration for clarity. Using the latest 2012/13 Survey data, national inequality measured by Theil index is 0.46008. If we deduct the income of each household in the 5th quintile by 0.483% and redistribute the proceeds equally among all households in the poorest quintile, the resultant Theil is 0.45388 (i.e. 0.46008–0.0062). Thus, an increase in disasters to affect one extra percentage point of people is equivalent to a half percent income tax on the richest fifth for redistribution to the poorest fifth. There is a significant positive impact of natural disasters that took place 4 years before the survey on income inequality. We interpret this result below. The inclusion of lags (up to 4 years) is supported by t-tests on the individual parameters. The Akaike and Bayesian Information Criteria do not support the inclusion of lags. If omitted, the instantaneous effect of natural disasters is smaller (−0.00486, p = 0.078) but not significantly so.

In our regressions, we cluster errors at district level. Since administrative policy implementation is mostly carried out at provincial level, we alternatively clustered at provincial level also considering the potential spatial correlation of natural disasters and found similar results (unreported).

4.2. Disaster impact on inequality of components of income

To disentangle the ways by which income inequality is decreased due to natural disasters, we decompose income into its components, and compute the Theil index for each component. Table 3 reveals that the negative impact of natural disasters on income inequality is not driven by receipts (which include any disaster relief payments) or by any foreign or domestic remittances households receive after disasters. Natural disasters and their immediate lags significantly decrease non-agricultural income inequality and non-seasonal agricultural income inequality, but increase seasonal agricultural income inequality. Given the strict labour laws which ensure the rights of employees in formal employment, Sri Lanka does not see any effect of natural disasters on employment income inequality.

Non-agricultural income and, to a lesser extent, receipts drive the positive impact after four years. Recall that a positive impact on the Theil index means that income inequality has increased. One possible explanation is that the poorest benefit most from government handouts after a disaster, and are disproportionally employed in the recovery effort. As emergency support is phased out and rebuilding complete, the poorest lose out after a delay.

Table 4 and Table 5 show the composition of household income varies across quintiles. Rich quintiles receive a higher share of their income from non-agricultural sources such as business activities and non-seasonal agricultural activities compared to the poor whilst the share of income the poor receive from these sources is much lower. Further, poorest households earn a higher share of

Table 3
Results for regressing income inequality on natural disasters, by income component.

	Dependent variable: Inequality – Component of income (Theil)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Income	Employment Income	Seasonal Agricultural Income	Non-Seasonal Agricultural Income	Non-Agricultural Income	Non-Monetary Income	Receipts	Remittances
Disaster	−0.00620**	0.000707	0.00200*	−0.00961**	−0.0112**	−0.00272	9.03e−05	0.00313
	(0.00252)	(0.000639)	(0.00117)	(0.00396)	(0.00525)	(0.00160)	(0.00155)	(0.00212)
Dis_lag1	0.000640	0.000133	−0.00100	0.00326	−0.000655	−0.000824	0.000355	0.000733
	(0.00106)	(0.000256)	(0.000695)	(0.00249)	(0.00146)	(0.000648)	(0.000630)	(0.000832)
Dis_lag2	−0.00338*	−0.000314	0.00209**	−0.00181	−0.00592**	0.000620	−0.00134	0.00183*
	(0.00166)	(0.000495)	(0.000884)	(0.00238)	(0.00248)	(0.000758)	(0.000907)	(0.000997)
Dis_lag3	−0.00414*	−0.000763	−0.00260	−0.0127***	−0.00525	−6.12e−05	0.000392	−0.000528
	(0.00208)	(0.000636)	(0.00287)	(0.00431)	(0.00569)	(0.00190)	(0.00150)	(0.00230)
Dis_lag4	0.00473**	−0.000156	0.00221	0.00513	0.0128**	−0.000331	0.00398**	−0.00101
	(0.00225)	(0.000623)	(0.00156)	(0.00515)	(0.00530)	(0.00148)	(0.00147)	(0.00164)
Dis_lag5	0.000189	0.000207	−0.000370	0.00153	0.000430	−0.00102	0.000755*	0.000590
	(0.00144)	(0.000244)	(0.000491)	(0.00200)	(0.00352)	(0.000682)	(0.000419)	(0.000611)
Observations	117	117	117	117	117	117	117	117
R-squared	0.186	0.114	0.244	0.251	0.112	0.510	0.515	0.156
Districts	25	25	25	25	25	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$

Table 4
Average share of income by components (%).

	Employment Income	Seasonal Agricultural Income	Non-Seasonal Agricultural Income	Non-Agricultural Income	Non-Monetary Income	Receipts
Q1	44.22	7.01	4.98	1.43	22.63	19.80
Q2	47.18	5.40	6.69	9.72	15.86	15.07
Q3	48.06	5.13	7.36	9.58	14.60	15.27
Q4	44.21	4.82	7.69	12.73	14.10	16.44
Q5	31.29	3.32	11.83	24.48	11.53	17.43
Disaster Impact		↑	↓	↓		

Notes: Q1–Q5 are the income quintiles. Arrows indicate the disaster impact on inequality of components of income (upward arrow for increase and downward arrow for decrease).

Table 5
Share of income by component (%) and disaster impact on inequality of components of income.

		Employment Income	Seasonal Agricultural Income	Non-Seasonal Agricultural Income	Non-Agricultural Income	Non-Monetary Income	Receipts	Total
1990/91	Q1	43.28	7.94	6.34	6.55	15.76	20.21	
	Q2	48.58	6.49	7.99	9.08	12.30	15.47	
	Q3	50.26	6.44	8.79	8.07	11.74	14.70	
	Q4	46.39	6.34	9.09	12.56	12.00	13.56	
	Q5	34.74	4.67	10.21	25.36	11.98	12.86	
1995/96	Q1	46.38	7.42	5.97	1.12	20.78	18.39	
	Q2	49.59	6.08	7.63	9.21	15.24	12.37	
	Q3	51.42	4.70	7.46	9.93	14.40	12.01	
	Q4	48.77	3.90	7.11	12.14	14.76	12.99	
	Q5	41.95	2.18	7.95	21.51	14.32	12.29	
2002	Q1	71.20	8.71	6.37	−45.57	38.31	21.00	
	Q2	52.61	4.19	6.21	9.81	17.35	9.76	
	Q3	50.84	3.68	6.66	10.87	16.72	11.30	
	Q4	47.58	2.98	6.24	12.84	16.77	13.46	
	Q5	35.23	1.82	8.34	22.20	14.13	18.17	
2006/07	Q1	45.49	4.59	3.78	−3.32	32.75	16.76	
	Q2	45.55	3.03	4.43	10.42	22.88	13.62	
	Q3	43.78	2.59	5.17	12.41	19.79	16.19	
	Q4	40.23	1.95	6.17	13.99	17.90	19.75	
	Q5	28.39	1.36	13.08	20.11	10.40	26.45	
2009/10	Q1	46.15	6.13	1.99	−10.47	36.81	19.37	
	Q2	43.21	4.26	4.17	10.74	22.64	14.88	
	Q3	42.50	3.77	5.06	12.31	20.00	16.48	
	Q4	39.75	3.09	5.36	12.53	17.91	21.52	
	Q5	22.45	1.75	16.47	28.69	10.08	20.58	
2012/13	Q1	42.37	4.10	0.89	−4.84	37.95	19.58	
	Q2	43.96	3.12	4.40	11.23	21.70	15.57	
	Q3	44.56	2.47	4.54	11.97	19.12	17.35	
	Q4	39.90	2.09	5.12	12.97	16.89	23.06	
	Q5	26.62	1.26	13.88	20.34	11.03	26.81	
Significant Impact	Dis		↑	↓	↓			↓
	Dis_lag1							
	Dis_lag2		↑		↓			↓
	Dis_lag3			↓				↓
	Dis_lag4				↑		↑	↑
	Dis_lag5						↑	

Notes: Q1–Q5 are the income quintiles. Arrows indicate the disaster impact on inequality of components of income (upward arrow for increase and downward arrow for decrease).

income from seasonal agriculture most probably weather dependent, compared to the richest quintile.

5. Robustness checks

5.1. Balanced panel

The number of districts covered in the survey changes over time as some districts of Northern and Eastern provinces were not covered in earlier waves due to the ongoing civil war at that time. To ensure that results are not driven by the newly added districts, we rerun our baseline regression with a balanced panel of 17 districts for the six waves. Results as presented in Table 6 support our original findings although the significance level of coefficients on the variables of interest is lower compared to the base model.

5.2. Additional controls

The above results hold in the presence of other control variables, namely, real median household income (in constant 2006 Rs.), poverty head count index (HCI) and the share of poor households (Table 7). The HCI is the percentage of population below the official poverty line, which is based upon the real total expenditure per person per month; a household with members whose per

Table 6
Results for regressing income inequality on natural disasters: Base model with a balanced panel of 17 districts.

	Dependent variable: Income inequality (Theil) Fixed Effects
Disaster (% Population Affected)	−0.00651*
	(0.00345)
Disaster_lag1	0.000532
	(0.000992)
Disaster_lag2	−0.00218
	(0.00177)
Disaster_lag3	−0.00687*
	(0.00348)
Disaster_lag4	0.00122
	(0.00306)
Disaster_lag5	−0.000260
	(0.00183)
Observations	102
Number of Districts	17
R-squared	0.204

Notes: Balanced panel of 17 districts with district level inequality measures for six waves of surveys, corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

Table 7
Results for regressing income inequality on natural disasters: Controls.

	Dependent variable: Income inequality (Theil)	
	(1)	(2)
Disaster (% Population Affected)	−0.00805***	−0.00947***
	(0.00224)	(0.00300)
Disaster_lag1	−0.000313	−0.000435
	(0.00134)	(0.00165)
Disaster_lag2	−0.00308**	−0.00404
	(0.00134)	(0.00249)
Disaster_lag3	−0.00585**	−0.00831*
	(0.00268)	(0.00450)
Disaster_lag4	0.00650**	0.00504
	(0.00260)	(0.00311)
Disaster_lag5	0.000152	9.85e−06
	(0.00132)	(0.00113)
Real Median Household Income (logged)	0.0986	−0.0799
	(0.237)	(0.281)
HCI	0.0190*	
	(0.00950)	
% of Poor Households		0.0174
		(0.0113)
Observations	117	100
R-squared	0.245	0.203
Number of Districts	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

capita expenditure is below the official poverty line is considered as a poor household (Department of Census & Statistics, 2015).

5.3. Alternative inequality metrics

We check whether our results hold for different inequality measures such as Gini coefficient, inter quintile range for average income and inter quartile range. As shown in Table 8, disasters and their immediate lags reduce income inequality not only measured by the Theil index but also by the Gini coefficient and the inter quintile range of average income. Further, disasters occurred in the previous year seem to significantly reduce inter quartile range of income.

Table 8
Results for regressing income inequality on natural disasters: Alternative inequality metrics, Gini coefficient, inter quintile range (IQ^5R), and inter quartile range (IQ^4R).

	Dependent variable: Income inequality		
	(1) Gini	(2) IQ^5R (ln)	(3) IQ^4R (ln)
Disaster (% Pop. Affected)	−0.00139***	−0.00453***	0.000759
	(0.000396)	(0.00126)	(0.000718)
Disaster_lag1	−3.73e−05	−0.000605	−0.000764**
	(0.000242)	(0.000991)	(0.000279)
Disaster_lag2	−0.000596**	−0.00235**	−0.000268
	(0.000227)	(0.000948)	(0.000593)
Disaster_lag3	−0.00128**	−0.00557**	−0.000123
	(0.000531)	(0.00210)	(0.000646)
Disaster_lag4	0.00156**	0.00627**	0.000621
	(0.000646)	(0.00275)	(0.00184)
Disaster_lag5	2.73e−05	−0.000245	4.59e−05
	(0.000214)	(0.000830)	(0.000378)
Real Median Household Income (logged)	−0.0584	0.570*	0.629**
	(0.0490)	(0.285)	(0.230)
HCI	0.00252	0.00512	−0.00391
	(0.00152)	(0.00850)	(0.00312)
Observations	117	117	117
R-squared	0.411	0.808	0.945
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$. IQ^4R (ln) is the natural logarithm of the inter quartile range or the income difference between the 75th percentile and the 25th percentile. IQ^5R (ln) is the natural logarithm of the difference between the average incomes of the fifth and first quintiles.

When we run the regression for alternative inequality measures with current disasters and additional relevant controls on access to safe drinking water and hygienic facilities, structure of the house and possession of movable properties which reflect socio-economic status of households, we observe that current disasters significantly decrease income inequality measured by alternative inequality metrics (Table 9).

5.4. Outliers

We exclude the survey wave 2006/07 which was after the Indian Ocean tsunami in December 2004 and the survey wave 2009/10 which was after the ending of 30 years long civil war alternatively and simultaneously, results remain significant and qualitatively similar (Table 10). Excluding the post-tsunami data somewhat reduces the value of the key parameter of interest, but the difference with the results in Table 3 is not significant. Excluding the post-war data has a larger, but insignificant effect. Excluding both post-war and post-tsunami data has the largest effect, but we cannot reject the hypothesis that the contemporaneous effect of natural disasters on income inequality are the same in Column 3 of Table 10 and Column 1 of Table 3.

5.5. Alternative estimators

The above results are consistent, but our specification may suffer from potential simultaneity as the dependent variable, income inequality may be indirectly influencing the percentage of population affected due to disasters. We therefore check the validity of results with alternative estimators. Accordingly, as a further robustness check, we re-estimate the model using ordinary least squares (OLS) and, difference and system generalised method of

Table 9
Results for regressing income inequality on natural disasters: Current disasters with additional controls.

	Dependent variable: Income inequality		
	(1) Theil	(2) Gini	(3) IQ^5R (ln)
Disaster (% Pop. Affected)	−0.0151***	−0.00209***	−0.00912***
	(0.00492)	(0.000736)	(0.00243)
% of Households without safe drinking water	0.0140*	0.00219*	0.00483
	(0.00757)	(0.00122)	(0.00502)
% of Households without a toilet	−0.0161	−0.00364	−0.0207
	(0.0310)	(0.00529)	(0.0199)
% of Households with no rooms	−0.0532	−0.00588	0.0117
	(0.0513)	(0.00909)	(0.0345)
% of Households without electric equipment	0.0210	0.00124	−0.000979
	(0.0128)	(0.00203)	(0.00825)
% of Households without vehicles	−0.00183	0.00136	−0.00370
	(0.0120)	(0.00198)	(0.00772)
Observations	61	61	61
R-squared	0.232	0.202	0.177
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***p < .01, **p < .05, *p < .1. IQ^5R (ln) is the natural logarithm of the difference between the average incomes of the fifth and first quintiles.

Table 10
Results for regressing income inequality on natural disasters: Excluding possible outlier waves.

	Dependent variable: Income inequality (Theil)		
	(1) Without wave just after Tsunami	(2) Without wave after ending of war	(3) Without both waves
Disaster (% Pop. Affected)	−0.00541**	−0.00399*	−0.00116*
	(0.00260)	(0.00230)	(0.000617)
Disaster_lag1	0.000326	0.00104	0.000493
	(0.00105)	(0.00115)	(0.000786)
Disaster_lag2	−0.00174*	−0.00260	0.000246
	(0.000921)	(0.00174)	(0.00144)
Disaster_lag3	−0.00229	−0.00416**	−0.00750**
	(0.00350)	(0.00169)	(0.00298)
Disaster_lag4	0.00504**	0.00298	−2.12e−05
	(0.00200)	(0.00184)	(0.00325)
Disaster_lag5	0.00226	−0.000598	−0.000578
	(0.00406)	(0.00107)	(0.00116)
Observations	98	95	76
R-squared	0.228	0.212	0.367
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for five waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***p < .01, **p < .05, *p < .1.

moments (GMM) estimators, dynamic panel estimators which use GMM procedure. The difference GMM estimator which uses the lagged level variables as GMM-style instruments in a more desirable way was proposed by Arellano and Bond (1991). A main advantage of this method is that it does not reduce the panel length as the instrumentation is done on period by period basis. By enhancing and refining this estimator further, Arellano and Bover (1995) and Blundell and Bond (1998) introduced system GMM. These estimators are especially useful when the panel is short. As discussed in Roodman (2006), these estimators are designed to use with panel data when the explanatory variables are not strictly exogenous (if it is suspected that they are correlated with past and possibly current realizations of the error) and suitable instrument variables are not available (McDermott et al., 2014).

As apparent from Table 11, alternative estimators, OLS and system GMM yield consistent results. Difference GMM also yields consistent results at least with respect to the sign on the coefficient. In this exercise, we restrict our explanatory variables to current disasters and HCI. The GMM uses lagged values of independent variables which are not strictly exogenous as internal instruments. Therefore, the inclusion of additional disaster lags in the model may complicate the process.

5.6. Disaster impact on income

As shown in Table 12, current natural disasters negatively affect mean household income whilst the disasters occurred in the previous year negatively affect median household income. Income of the poorest quintile is reduced by current disasters and disasters occurred three years before. Income of the middle quintiles is reduced by the disasters occurred in the previous year. Richest quintile's income is decreased by current disasters and disasters occurred two and three years before. So, we find clear evidence that income of all the quintiles is affected by natural disasters.

These results together with the results of the base model in Column 1 of Table 3 show how changes in income levels of different quintiles feed into the changes of overall income inequality due to natural disasters. Current disasters negatively affect the income of the poorest quintile as well as the income of the richest quintile. Although the decreases in income suffered by poorest and richest quintiles may not considerably differ as a percentage of their income, absolute income losses would be substantially different for these two groups. When the absolute income loss suffered by rich quintile far exceeds the absolute income loss of the poorest quintile, the net result would be a smaller difference between the incomes of these two groups leading to a decrease in income inequality. This is exactly what we see from the results of the base model with respect to the current disaster impact on income inequality.

5.7. Disasters and household expenditure inequality

We repeat our analysis for household expenditure inequality. As in the previous analysis, we calculate per adult equivalent household expenditure and then calculate district wise inequality measures for each survey wave. When we estimate our baseline specification using panel fixed effects estimator, we do not find any impact of natural disasters on expenditure inequality measured either by Theil index or Gini coefficient (Table 13). There may be two plausible explanations for this. One is that households suffer income losses due to natural disasters disproportionately across quintiles, however, they act as if they have a permanent income when it comes to expenditure and therefore do not change their spending behaviour. The other is that all the households reduce their expenditure proportionately across quintiles in the presence of natural disasters. Both scenarios would lead to no change in expenditure inequality among households due to natural disasters.

5.8. Disaster Sub-Groups and income inequality

Climatic, hydrological, geophysical, meteorological, oceanic or biological sources acting individually or in combination can give rise to a natural disaster. Considering the origin and characteristics of natural disasters, the international disaster database (EM-DAT) classifies natural disasters into sub-groups, namely, biological, climatic, hydrological, geophysical and meteorological disasters.

Table 11
Results for regressing income inequality on natural disasters: Alternative estimators.

	Dependent variable: Income inequality (Theil)			
	(1) FE	(2) OLS	(3) Diff. GMM	(4) Sys. GMM
Disaster (% Pop. Affected)	−0.00621**	−0.00362**	−0.00509	−0.00821**
	(0.00275)	(0.00152)	(0.00363)	(0.00363)
HCI	0.0147	0.00284	0.0166	0.0182
	(0.00910)	(0.00361)	(0.0128)	(0.0146)
Observations	117	117	92	117
R-squared	0.198	0.115		
Number of Districts	25		22	25
Number of Instruments			10	11
Arellano-Bond Test AR(1)			0.067	0.088
Arellano-Bond Test AR(2)			0.714	0.652
Hansen Test			0.234	0.213

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***p < .01, **p < .05, *p < .1. Lags used to instrument the endogenous variables in system GMM regression limited to 10.

Table 12
Results for regressing income on natural disasters.

	Dependent variable: Household income (logged)						
	(1) Mean	(2) Median	(3) Q1	(4) Q2	(5) Q3	(6) Q4	(7) Q5
Disasters	−0.00507**	−0.00180	−0.0109***	−0.00212	−0.00172	−0.00152	−0.00613***
	(0.00185)	(0.00154)	(0.00387)	(0.00159)	(0.00163)	(0.00166)	(0.00186)
Dis_lag1	−0.000724	−0.00101***	0.00151	−0.00102***	−0.00108***	−0.00127***	−0.000596
	(0.000537)	(0.000299)	(0.00205)	(0.000331)	(0.000292)	(0.000301)	(0.000832)
Dis_lag2	−0.00104	0.000328	0.00104	0.000502	0.000298	0.000107	−0.00209**
	(0.000691)	(0.000561)	(0.00127)	(0.000763)	(0.000567)	(0.000475)	(0.000945)
Dis_lag3	−0.00358*	−0.00124	−0.00598*	−0.00111	−0.000954	−0.000852	−0.00546**
	(0.00192)	(0.00141)	(0.00304)	(0.00174)	(0.00142)	(0.00134)	(0.00239)
Dis_lag4	0.00209	0.000165	0.00269	−5.09e−05	0.000146	0.000795	0.00485*
	(0.00157)	(0.00117)	(0.00263)	(0.00112)	(0.00113)	(0.00133)	(0.00235)
Dis_lag5	0.000563	0.000395	0.00180	0.000293	0.000355	0.000348	0.000333
	(0.000797)	(0.000424)	(0.00114)	(0.000473)	(0.000437)	(0.000508)	(0.000967)
Observations	117	117	113	117	117	117	117
R-squared	0.852	0.905	0.414	0.882	0.907	0.922	0.799
Districts	25	25	24	25	25	25	25

Notes: Panel of district level measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***p < .01, **p < .05, *p < .1.

Table 13
Results for regressing expenditure inequality on natural disasters.

	Dependent variable: Expenditure inequality	
	(1) Theil	(2) Gini
Disaster (% Population Affected)	0.00116	0.000239
	(0.00145)	(0.000318)
Disaster_lag1	0.000136	4.41e−05
	(0.000130)	(8.06e−05)
Disaster_lag2	0.000427	0.000205
	(0.000321)	(0.000146)
Disaster_lag3	−5.63e−05	−5.06e−05
	(0.000434)	(0.000255)
Disaster_lag4	−0.00124	−0.000379
	(0.00131)	(0.000578)
Disaster_lag5	6.81e−05	6.54e−05
	(0.000172)	(6.67e−05)
Observations	117	117
R-squared	0.321	0.514
Number of Districts	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***p < .01, **p < .05, *p < .1.

In terms of the definitions given by EM-DAT, a biological disaster is a hazard caused by the exposure to living organisms and their toxic substances or vector-borne diseases that they may carry. Epidemics of bacterial, parasitic and viral diseases, and plagues are categorized under this sub-group. A hazard caused by long-lived meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variables is defined as a climatic disaster. Accordingly, droughts are regarded as climatic disasters. A geophysical disaster is defined to be a hazard originating from solid earth such as earthquakes, land subsidence and tsunamis. A hydrological disaster is a hazard caused by occurrence, movement, and distribution of surface and subsurface freshwater and saltwater. Floods, heavy rains and landslides are categorized under this sub-group. A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days is defined to be a meteorological disaster. Examples for this sub-group are cyclones, gales, storms, strong winds, and tornados.

The impact of natural disasters may vary according to the disaster magnitude, intensity, frequency, extent of the exposure and duration. For instance, while earthquakes are generally of a shorter life span restricted to a small locality, droughts can be prolonged and they can affect much larger regions compared to earthquakes. Further, the magnitude of disaster impact is also dependent on the conditions of vulnerability, coping and mitigating capacities, and levels of adaptation prevailing in the affected territories.

Accepting the fact that natural disasters differ in nature, intensity, duration and impact, we repeat our analysis by disaster subgroups. Table 14 shows a significant negative impact of geophysical, hydrological and meteorological disasters on different income inequality measures.

Some argue that biological disasters are very different from other natural disasters. The main reason for this is that biological crises only harm human beings and other living organisms whilst other natural disasters damage property in addition. Further, occurrence of natural disasters such as earthquakes, hurricanes, tsunamis is beyond human control, they can only lessen the damage through action for preparation and mitigation. Although, the inception of biological disasters is uncontrollable, their impact and spread mostly dependent on early human intervention (Lerbinger, 2014). We therefore replicate the analysis excluding biological disasters from total disasters. This exercise derives similar results as for the base model (see Table 15).

As shown in Table 16, different natural disaster subgroups affect mean, median household incomes and income across quintiles differently. Meteorological disasters may appear to increase income inequality on the face of results, as the relative loss due to such disasters decreases with income. Nevertheless, we do not find evidence to that effect; see Table 14. As a further step, we rerun our regression excluding meteorological disasters from total disasters to ensure that it is not linked with the metrics being used (Table 17). Results are very similar to the base model's results.

Table 15
Disasters excluding biological disasters and income inequality.

	Dependent variable: Income inequality (Theil) Fixed Effects
Disaster (% Population Affected)	−0.00624**
	(0.00256)
Disaster_lag1	0.000627
	(0.00106)
Disaster_lag2	−0.00341*
	(0.00167)
Disaster_lag3	−0.00421*
	(0.00209)
Disaster_lag4	0.00465*
	(0.00226)
Disaster_lag5	0.000184
	(0.00144)
Observations	117
Number of Districts	25
R-squared	0.186

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses.

6. Discussion and conclusion

We explore the impact of natural disasters on income inequality in Sri Lanka at district level, the first study of this nature for the country. We construct a unique panel dataset for the purpose that includes inter alia district wise inequality/income measures and percentages of population affected due to natural disasters in each district for the six survey periods of the HIES series between 1990 and 2013. Using panel fixed effects estimator as the main empirical strategy we find that contemporaneous natural disasters and their immediate lags decrease district level income inequality as measured by the Theil index, and substantially so. These results are robust across alternative inequality metrics, sub-samples and alternative estimators. However, we do not find any evidence to the effect that natural disasters affect household expenditure inequality. This is possible if households do not change their expenditure patterns despite their income being affected by disasters or if they might reduce their expenditure proportionately across income quintiles as a result of disaster consequences.

Further analyses suggest that although natural disasters negatively affect household income across all the quintiles, rich quintiles disproportionately bear direct disaster damages at a higher cost. Even though the poor are more vulnerable to disasters, when the poor live a subsistence lifestyle and if they do not possess or own much material assets, their losses will be less compared to the rich. Rich may lose income deriving capital assets more due to destruction and through sale as a coping strategy. On the other hand, if the poor are mainly engaged in low-skilled or unskilled labour they can easily diversify their income sources in the aftermath of a natural disaster. Whilst the rich may suffer profit losses, disasters may open the poor a door for new opportunities. It is evident from our decomposition results that natural disasters decrease non-agricultural income inequality and non-seasonal agricultural income inequality. Household income composition shows that the richest quintile receives a much higher share of

Table 14
Results for regressing income inequality on natural disasters by disaster type.

	Dependent variable: Income inequality			
	(1) Theil	(2) Gini	(3) IQ^4R (ln)	(4) IQ^5R (ln)
Biological	0.0645	0.00520	0.0447*	0.0157
	(0.146)	(0.0198)	(0.0238)	(0.0782)
Climatic	−0.00411	−0.000545	0.000362	−0.00149
	(0.00328)	(0.000485)	(0.00144)	(0.00128)
Geophysical	−0.181*	−0.0587***	−0.0250	−0.185***
	(0.0879)	(0.0144)	(0.0201)	(0.0558)
Hydrological	−0.00729	−0.00123	−0.00261	−0.00875**
	(0.00574)	(0.00135)	(0.00246)	(0.00398)
Meteorological	−0.00102	−5.91e−05	−0.00760***	−0.0115***
	(0.00443)	(0.00100)	(0.00153)	(0.00227)
Observations	117	117	117	117
R-squared	0.164	0.333	0.902	0.786
Number of Districts	25	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. IQ^4R (ln) is the natural logarithm of the inter quartile range or the income difference between the 75th percentile and the 25th percentile. IQ^5R (ln) is the natural logarithm of the difference between the average incomes of the fifth and first quintiles. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***$p < .01$, **$p < .05$, *$p < .1$.

Table 16
Different disaster sub-groups and income.

	Dependent variable: Household Income (logged)						
	(1) Mean	(2) Median	(3) Q1	(4) Q2	(5) Q3	(5) Q4	(7) Q5
Biological	0.0443	0.0398***	−0.0268	0.0300***	0.0360***	0.0276*	0.0283
	(0.0599)	(0.0117)	(0.0374)	(0.00981)	(0.0111)	(0.0140)	(0.0805)
Climatic	−0.00368*	−0.00117	−0.0111**	−0.00141	−0.00101	−0.000659	−0.00347
	(0.00213)	(0.00124)	(0.00478)	(0.00111)	(0.00128)	(0.00131)	(0.00207)
Geophysical	−0.110***	0.0361*	−0.430***	0.0227	0.0339*	0.0152	−0.202***
	(0.0318)	(0.0188)	(0.0601)	(0.0182)	(0.0187)	(0.0178)	(0.0516)
Hydrological	−0.00587***	−0.00287	−0.00595	−0.00350	−0.00317	−0.00320	−0.00826**
	(0.00184)	(0.00232)	(0.00424)	(0.00236)	(0.00240)	(0.00234)	(0.00371)
Meteorological	−0.0118***	−0.00962***	−0.0137***	−0.0118***	−0.00980***	−0.00950***	−0.0124***
	(0.00151)	(0.00176)	(0.00331)	(0.00185)	(0.00181)	(0.00165)	(0.00259)
Observations	117	117	113	117	117	117	117
R-squared	0.847	0.903	0.413	0.883	0.905	0.918	0.788
Districts	25	25	24	25	25	25	25

Notes: Q1–Q5 are the income quintiles. Panel of district level measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. ***p < .01, **p < .05, *p < .1

Table 17
Disasters excluding meteorological disasters and income inequality.

	Dependent variable: Income inequality (Theil) Fixed Effects
Disaster (% Population Affected)	−0.00646**
	(0.00248)
Disaster_lag1	0.000460
	(0.00101)
Disaster_lag2	−0.00281*
	(0.00156)
Disaster_lag3	−0.00524**
	(0.00219)
Disaster_lag4	0.00463**
	(0.00219)
Disaster_lag5	9.24e−05
	(0.00136)
Observations	117
Number of Districts	25
R-squared	0.187

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses.

their income from these very activities compared to the poor. When the rich suffer greater losses in profits and income due to disasters, it is inevitable that household income inequality would decrease, however, at the expense of the rich. Our findings warrant policies to safeguard the interests of middle and higher income groups in disaster consequences. Further, policy makers should give sufficient consideration to natural disasters in designing and implementing policies to promote poverty reduction and inclusive economic growth.

To achieve effective poverty reduction and inclusive growth, the desired is a lower inequality in general. McKay and Pal (2004) present evidence that lower initial inequality has a favourable influence on subsequent consumption across many Indian states. Our study showed that natural disasters lead to lesser income inequality. Our data allowed us to decompose income inequality into components of income so that mechanisms are understood better. This exercise showed that the reduction in income inequality was not derived through enhanced receipts or remittances. Natural disasters decreased non-seasonal agricultural income inequality and non-agricultural income inequality. But, disasters increased seasonal agricultural income inequality. This is explained by the fact that income of richer households is mainly derived from non-agricultural sources such as manufacturing and business activities and non-seasonal agricultural activities. In contrary, poorer households have a higher share of agricultural income. So, it is clear that the resultant lower income inequality does not reflect an increase in the income of the poorest quintile but a decrease in the income of the rich quintiles. Although, lower income inequality is desirable for poverty reduction and to achieve inclusive growth, as a low income inequality derived through higher damages caused to middle and richer quintiles does not reflect distributive justice, change of inequality in the face of natural disasters should be read with caution.

Every effort has been exerted to include all monetary and non-monetary income derived from all sources, in calculations. However, free State services such as education and health the value of which cannot be imputed easily and exactly, are not included in the income. Further, the OECD modified equivalence scale which was used to arrive at per adult equivalent income/expenditure does not take into consideration some household characteristics, such as health status and disabilities of household members that affect specific household needs and capacities. These may pose biases in estimations, however, these are common issues to any household survey.

Our study does not capture potential internal migration as a result of natural disasters which would otherwise have explained the decrease in income inequality. This would be a limitation to our analysis. Future research can address this issue although this study is constrained with data availability. We aggregated household data to district level as we are interested in inequality. Follow-up research could construct a pseudo-panel of households, and use quantile regression to analyze the impact of natural disasters on households across the income spectrum. Further, Sri Lanka is just one country out of many that face various natural disaster consequences and issues relating to distributive justice at the same time. Furthermore, as Sri Lanka is a lower middle-income country with an economy oriented towards services and industry, it could not represent lower income countries which mainly depend on agriculture and are more vulnerable to disasters. Therefore, this analysis could be repeated for other countries with better data as an avenue for future research.

Furthermore, recent research (Patankar, 2017) suggests that frequent urban and flash floods severely affect very poor individuals, especially, people who live in temporary huts, slums, shanties and single-storied buildings, repeatedly. It is believed that these events do not enter formal databases in the normal course, but their impact on poor people could be large, especially through health effects. Also, such disasters could negatively impact the income of the poor through missed days of work. This would cause biases in the estimations. Therefore, this analysis could be repeated with carefully collected broadened primary data.

Conflict of interest

None declared.

Acknowledgements

We gratefully acknowledge the funding received from RISES-AM, EU Research Project [Grant No. 603396]. We are thankful to the Disaster Management Centre and the Department of Census and Statistics both of Sri Lanka for data. We are grateful to the participants of 2017 Sussex Economics PhD Conference for their helpful comments. We are also grateful to Stéphane Hallegatte, Senior Economist, Climate Change Group, World Bank, three anonymous referees and the editor for their insightful comments.

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