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Economic Disasters and Inequality

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Economic Disasters and Inequality

Bruno Ćorić♠ and Rangan Gupta♦

Abstract

This paper analyses the dynamic effects of economic disasters, captured by cumulative decline in output of at least 10 percent over 1 or more years, on disposable income inequality of a sample of 99 countries over the annual period of 1960 to 2017. Based on impulse response functions derived from a robust local projections method, we find that economic disasters increase inequality by 4%, with the overall effect being statistically significant and highly persistent over a period of 20 years following the shock. When we repeat the analysis by categorizing the 99 countries based on income groups and regions, we find that the strongest effects are felt by high-income countries (8%), and in Europe, Central Asia and North America (16%) taken together, as primarily driven by ex-socialist economies. Though of lesser magnitude, statistically significant increases in inequality are also observed for low-, and upper-middle-income economies, and the regions of Latin America and Caribbean, Middle East and North Africa (MENA) and South Asia, and to some extent also for Sub-Saharan Africa. Our findings have important policy implications.
Keywords: inequality; economic disasters; local projection method

JEL codes: C22, D63, Q54

1. Introduction

The objective of this paper is to analyse the dynamic impact of economic disasters on income inequality of 99 countries over the annual period of 1960 to 2017. In this regard, we utilize an improved version of the local projection method of Jordà (2005), and investigate the evolution of inequality following the impact of a shock associated with economic disaster events for all the countries in the sample, as well as for countries categorized as per income and regional location. Understandably, the idea behind the sub-sample analyses are to detect possible heterogeneous impact, and draw appropriate groups-specific policy conclusions in the process.

In this regard, note that, Barro (2006) uses the term "economic disasters" to identify especially large economic crises, later defined as a cumulative decline in consumption or output of at least 10 percent over 1 or more years. Given this, economic crises can be linked to income inequality through the effect of slowed economic growth, investment and rising unemployment of the lower income classes, as well as through lower wages linked to the weakened bargaining power of labor during crises (see the discussions in Ćorić (2018), and Ćorić and Šimić (2021)). Put alternatively, in the wake of such negative aggregate shocks (irrespective of their underlying reason(s)), it is not incorrect to expect the rich to smooth faster their income and consumption to the pre-shock levels due to their existing higher endowment levels relative to the poor, resulting in more skewed income distributions, i.e., higher-levels of inequality.

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While many studies have related inequality to financial crises and natural disasters due to climate change (see for example, Bodea et al. (2021) and Cappelli et al. (2021) and references cited there in), realizing that economic crises can also be caused by geopolitical events (Berkman et al., 2017) and outbreaks of contagious diseases (Bouri et al., 2022), our study is relatively broader than the existing literature in terms of identifying disaster risks. To the best of our knowledge, our paper makes the first attempt to understand the dynamic impact of economic disasters on inequality. The only other available (working) paper in this regard is of Atkinson and Morelli (2011), wherein the authors used an event study-based approach involving a window of +/- 5 years around declines of 10 percent of gross domestic product (GDP) per capita and consumption per capita for a set of 24 countries, to depict weak effects of economic disasters on inequality over the period of 1911 to 2006.

The remainder of the paper is organized as follows: Section 2 discusses our data set and methodology. Section 3 presents the empirical findings, with Section 4 concluding the paper.

2. Data and Methodology

To improve our understanding of the relationship between inequality and economic disasters we employ the country level annual data on the Gini index of economic inequality based on disposable (post-tax, post-transfer) income, and obtained from the Standardized World Income Inequality Database (SWIID). The SWIID, as developed by Solt (2020), currently incorporates comparable Gini indices for 198 countries for as many years as possible from 1960 to 2020.[1] The data on economic disasters are retrieved from a new datasets on economic disasters in the post-WWII period constructed by Ćorić (2021, 2022). The data on economic disasters are available for 212 countries from 1950 to 2017. Following Barro and Ursúa (2008) economic disasters are identified by using annual GDP per capita and consumption per capita data separately, as cumulative declines in these two variables of at least 10 percent for over 1 or more years. Our focus will be the disasters identified using GDP per capita in the main text, while results from consumption per capita-based disasters will be presented in the Appendix of the paper.

To estimate the inequality dynamic after economic disasters we use Teulings and Zubanov's (2014) extension of the Jordà's (2005) local projection method. This method estimates the impulse response function (IRF) directly from the forecast equation for inequality *k* periods ahead. Even though Jordà's (2005) estimator is robust to specification errors (arising in shocks identified using the Cholesky/recursive scheme due to usage of more lags of the explanatory variables and higher length of the forecast horizon (Auerbach and Gorodnichenko, 2013)) , Teulings and Zubanov (2014) show that the method can be subject to bias that occurs due to the failure of the estimator to use information on the crises occurring within the forecast horizon. Therefore, to estimate the inequality dynamic after economic disasters we employ the following empirical panel autoregressive model of inequality comprising current, lagged and variables for economic disasters occurring within the forecast horizon (i.e., between *t* and *t*+*k*)::

$$I_{i,t+k} - I_{i,t-1} = \alpha_i^k + \sum_{j=1}^{4} \psi_j^k \Delta I_{i,t-j} + \sum_{l=0}^{4} \phi_l^k ED_{i,t-l} + \sum_{l=0}^{k-1} \delta_l^k ED_{i,t+k-l} + \varepsilon_{i,t+k} \quad (1)$$

where *I* denotes the logarithm of Gini index, while the *k* superscript represents the considered time horizon. *i* and *t* superscripts index countries and time, respectively. *ED* is the variable for

[1] The SWIID Version 9.3, (as of June 2022) is available for download from: https://fsolt.org/swiid/.

economic disasters, created as discussed above. It is a dummy variable that equals to 1 if an economic disaster in country i starts in year t and 0 otherwise. α_i, indicates country specific fixed effects, while $\varepsilon_{i,t}$ is the error term.

The employed local projection method estimates separate regressions for the horizons between time t and time $t+k$. The sequence of estimates on the current ED, ϕ_0^k, provides the average responses of the Gini index over the forecast horizon to an economic disasters. The corresponding serially correlation-robust standard errors are used to construct 95% confidence intervals.[2]

3. Results

We run a separate regression for each forecast horizon up to $k=20$. As both data samples are unbalanced we include only countries with at least 30 consecutive observations on the Gini index of inequality. Hence, our effective sample comprises 99 countries with 3,664 observations at $k=0$, with a complete list of countries being provided in the Table A1 in the Appendix of the paper. As the forecast horizon increases the effective sample size reduces gradually to 1,684 at $k=20$, but the number of countries in the sample remains constant.

Figure 1 plots the estimates of ϕ_0^k, from our overall sample of 99 countries that comprise 129 economic disasters identified as cumulative declines in GDP per capita of at least 10 percent over 1 or more years. The plotted results show the statistically significant increase of economic inequality after the onset of typical economic disaster. Particularly, the results indicate that an average economic disaster leads to a gradual increase of the Gini index reaching the maximum of 4.4%, 12 years after the start of economic disaster. The increase of inequality remains statistically significant and around 4% for the rest of the forecast horizon, with it declining to 3.3% at k=20. In other words, we do observe a significantly persistent effect of economic disasters on increases of inequality.

[INSERT FIGURE 1]

Figure A1 in the Appendix plots the estimates of ϕ_0^k, from the sample that comprise 203 economic disasters identified as cumulative declines in consumption per capita of at least 10 percent over 1 or more years. While a similar pattern of the effect on inequality is observed, the impact in general is comparatively smaller (i.e., below 4%), as observed with the case of the GDP per capita-based economic disasters.

Next, we revert back to the economic disasters identified via GDP per capita, but now we aim to look at its effects on inequality with countries categorized based on income groups (Low; Low-Middle; Upper-Middle; High)[3], and regions (East Asia and Pacific; Europe, Central Asia and North America; Latin America and Caribbean; Middle East and North Africa (MENA) and South Asia; Sub-Saharan Africa), with the results reported in Figures 2 and 3 respectively. As can be seen from the various sub-figures of Figures 2 and 3, the overall results are driven by high-income countries, as well as the region of Europe, Central Asia and North America, with the latter also representing high-income countries. In other words, this category of income and region are found to experience the strongest impact on inequality following economic disasters, registering peaks of 8% and 16% respectively, after 10 years following the shock. Also, as observed from Figure 2, significant increases in inequality are also observed

[2] The use of country fixed-effects rise a well-known issue of dynamic panel bias, but Teulings and Zubanov (2014) demonstrate that the bias is very small for panels with T=30 and above.

[3] The countries corresponding to these four income categories have been identified in Table A1.

for low-, and upper-middle-income countries. As far as regions are concerned, as can be seen from Figure 3, significant rises in inequality are also detected for Latin America and Caribbean, Middle East and North Africa (MENA) and South Asia, and to some extent also for Sub-Saharan Africa. Figures A2 and A3 in the Appendix reports qualitatively similar observations based on economic disasters detected using consumption per capita.

[INSERT FIGURES 2 AND 3]

In Figure 4, we delve a bit more into this issue of why we observe stronger effect for the high-income countries and that for the region of Europe, Central Asia and North America by excluding from them the ex-socialist economies. As can be observed now from Figures 4(a) and 4(c), when doing this separation, the inequality effects of GDP per capita-based disasters on the remaining countries in the high-income group and the Europe, Central Asia and North America region decreases substantially when compared to Figures 2(d) and 3(b), when the ex-socialist countries were not excluded. As revealed in Figures 4(b) and 4(d), the ex-socialist countries experience stronger impact of disasters relative to the corresponding categories of income and regions that excludes them.[4] This observation is understandable since, while communism had the "homogenising" effect of compressing income inequality, the fall of communism resulted in a rise in inequality in all ex-socialist countries, which in turn should not be surprising, given very (and to some extent artificially) low income inequality during communism (Novokmet, 2021). In other words, economic disasters tended to exacerbate the already high inequality that resulted from the end of communism, and transition of these countries into market economies.

[INSERT FIGURE 4]

4. Conclusion

As per the World Inequality Report in 2022 by the World Inequality Lab,[5] the richest 10% today snap up 52% of all income, with the poorest half getting just 8.5%. In sum, global inequalities are in bad shape and mostly do not appear to be getting better. Hence, understanding what drives income inequality is an important policy question. In this paper we analyses the role of the multifaceted nature of economic disasters, capturing economic crises, measured by the cumulative decline in output (GDP per capita) of at least 10 percent over 1 or more years, on disposable income inequality. Based on impulse response functions derived from a robust local projections method, applied to a sample of 99 countries over the annual period of 1960 to 2017, we find that economic disasters increases inequality by 4% in a statistically significant fashion, with the overall effect being highly persistent over a period of 20 years following the shock. When reconduct the analysis by categorizing the 99 countries based on income groups and regions, we find that the strongest effects are felt by high-income countries (8%), and in Europe, Central Asia and North America (16%) combined, and are primarily driven by ex-socialist economies. Statistically significant increases in inequality, but of relatively lesser size, are also observed for low-, and upper-middle-income economies, and the regions of Latin America and Caribbean, Middle East and North Africa (MENA) and South Asia, and to some extent also for Sub-Saharan Africa. Our results are robust, when we measure

[4] Similar conclusions are reached when we use declines in consumption per capita to measure economic disasters, with the results available upon request from the authors.
[5] See: https://wir2022.wid.world/download/.

economic disasters by the cumulative decline in consumption per capita (of at least 10 percent over 1 or more years).

In light of the seriousness of the issue of inequality globally, our findings have important implications, especially due to the persistent effect of economic disasters on income distribution detected by us. In particular, the avoidance of economic crises may be necessary to ensure the sustainability of the social institutions we have developed, such as the welfare state and the stability of democratic political governance, besides the undertaking of climate change-related policies to prevent natural disasters, and in the process keep inequality in check.

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Figure 1. Cumulative change in Gini index of economic inequality after economic disasters identified by using GDP per capita data

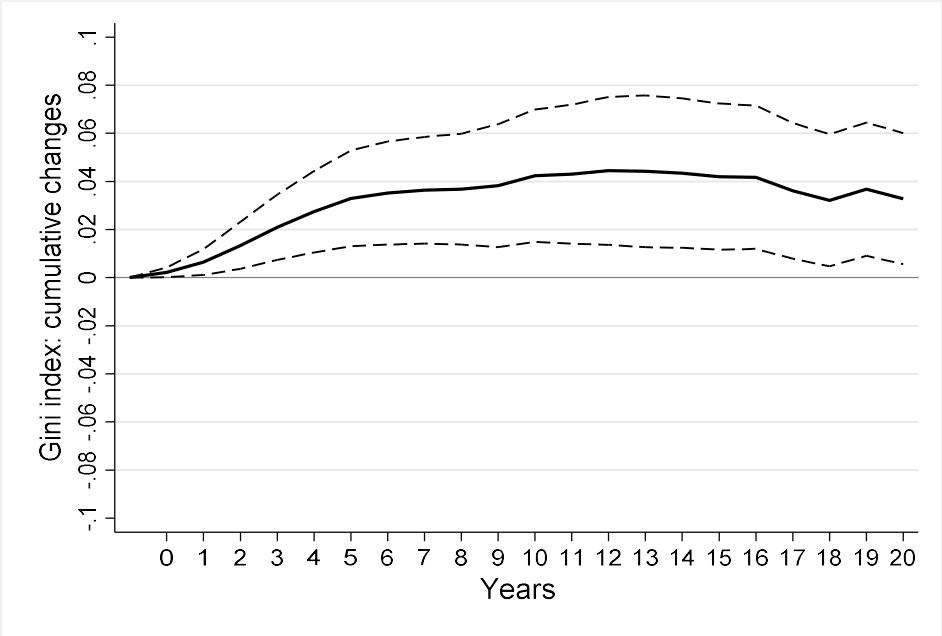
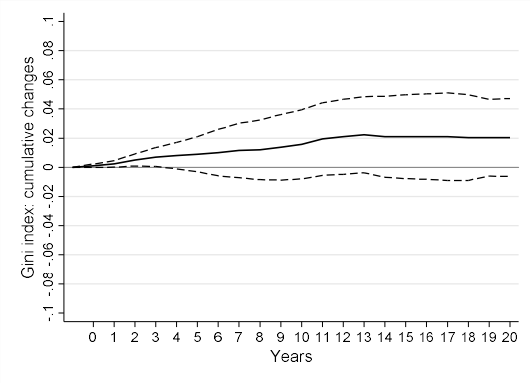
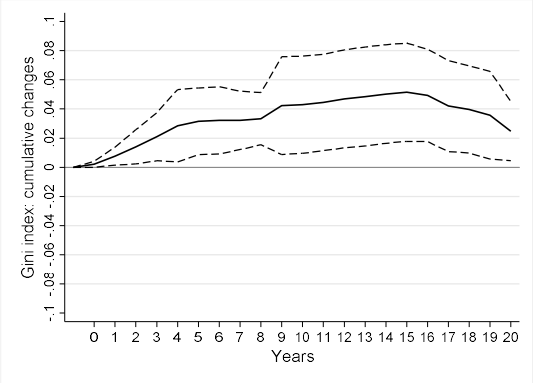


Figure 2. Cumulative change in Gini index of economic inequality as per income-category after economic disasters identified by using GDP per capita data

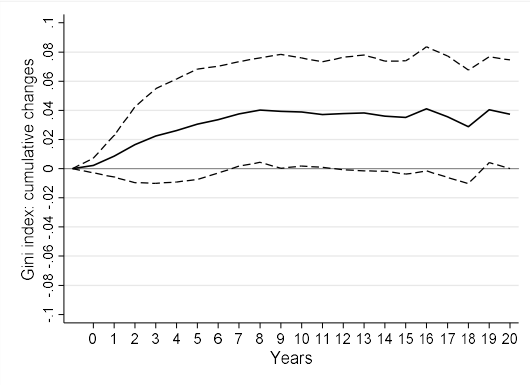
(a) Low income (6 countries, 25 disasters)



(b) Low-Middle Income (21 countries, 30 disasters)



(c) Upper-Middle Income (28 countries, 41 disasters)



(d) High Income (44 countries, 33 disasters)

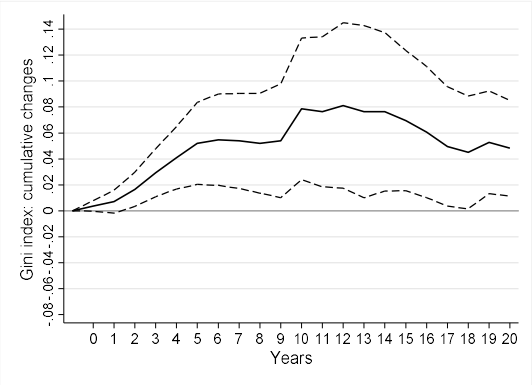
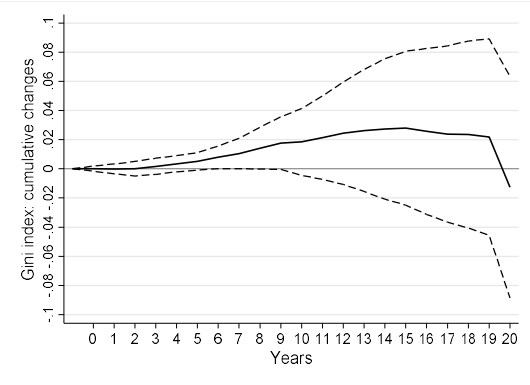
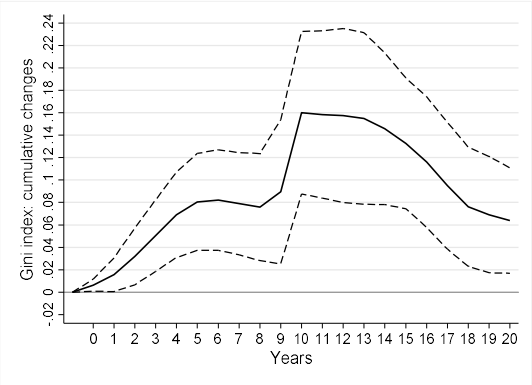


Figure 3. Cumulative change in Gini index of economic inequality as per region after economic disasters identified by using GDP per capita data

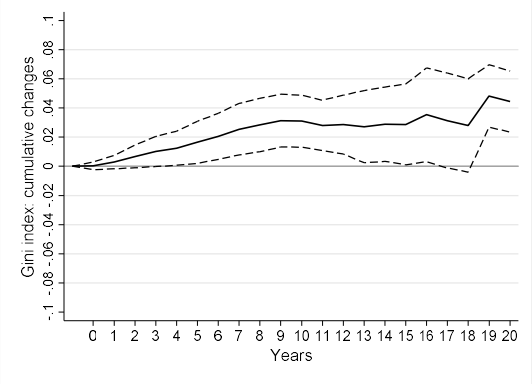
(a) East Asia and Pacific (14 countries, 9 disasters)



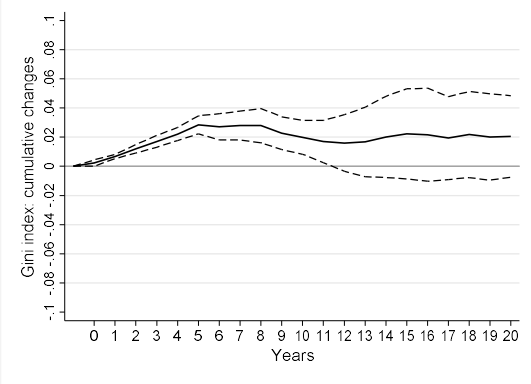
(b) Europe, Central Asia and North America (40 countries, 38 disasters)



(c) Latin America and Caribbean (18 countries, 27 disasters)



(d) Middle East and North Africa, and South Asia (11 countries, 13 disasters)



(e) Sub-Saharan Africa (16 countries, 42 disasters)

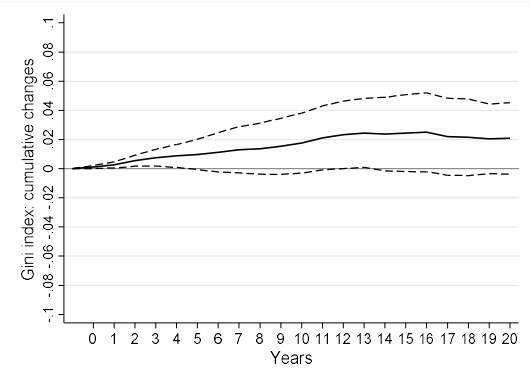
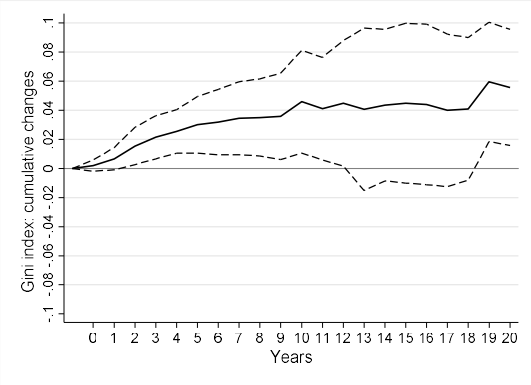
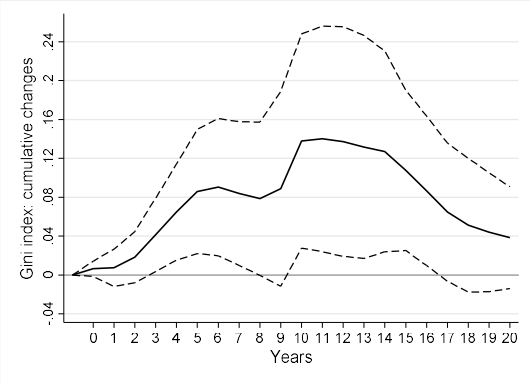


Figure 4. Cumulative change in Gini index of economic inequality as per income category and region after economic disasters identified by using GDP per capita data

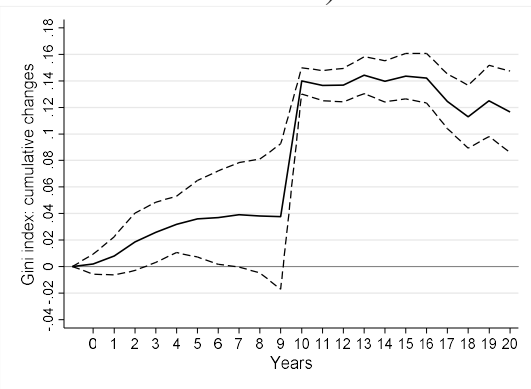
(a) High Income without Ex-Socialist Economies (34 countries, 18 disasters)



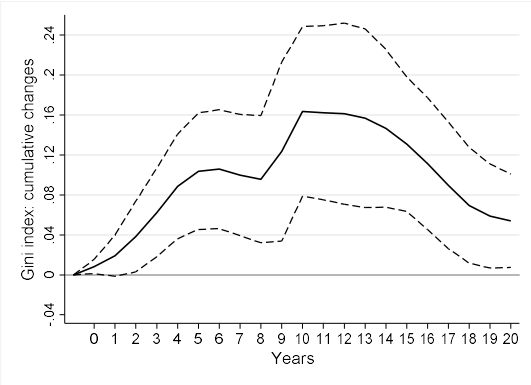
(b) Ex-Socialist Economies (10 countries, 15 disasters)



(c) Europe, Central Asia and North America without Ex-Socialist Economies (21 countries, 11 disasters)



(d) Ex-Socialist Economies (19 countries, 27 disasters)



Appendix

Table A1. List of countries

Argentina***	Czech Republic****	Israel****	Nepal**	South Africa***
Armenia***	Denmark****	Italy****	Netherlands****	Spain****
Australia****	Dominican Republic***	Jamaica***	New Zealand****	Sri Lanka**
Austria****	Egypt**	Japan****	Nigeria**	Sudan*
Bangladesh**	Estonia****	Jordan***	Norway****	Sweden****
Barbados****	Eswatini**	Kazakhstan***	Pakistan**	Switzerland****
Belarus***	Fiji***	Kenya**	Panama****	Taiwan****
Belgium****	Finland****	Korea****	Paraguay***	Tanzania**
Botswana***	France****	Kyrgyzstan**	Peru***	Thailand***
Brazil***	Georgia***	Latvia****	Philippines**	Tonga***
Bulgaria***	Germany****	Lesotho**	Poland****	Trinidad and Tobago****
Canada****	Ghana**	Lithuania****	Portugal****	Tunisia**
Chile****	Greece****	Luxembourg****	Puerto Rico****	Turkey***
China***	Guatemala***	Madagascar*	Romania****	Ukraine**
China, Hong Kong****	Honduras**	Malawi*	Russian Federation***	United Kingdom****
Colombia***	Hungary****	Malaysia***	Rwanda*	United States****
Costa Rica***	India**	Mauritius***	Sierra Leone*	Uruguay****
Cote d'Ivoire**	Indonesia**	Mexico***	Singapore****	Venezuela***
Croatia****	Iran**	Moldova***	Slovakia****	Zambia*
Cyprus****	Ireland****	Morocco**	Slovenia****	

Note: Low: *; Low-Middle: **; Upper-Middle: ***; High: ****. The categorization is based on the World Bank's income classification for the 2023 current fiscal year available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

Figure A1. Cumulative change in Gini index of economic inequality after economic disasters identified by using consumption per capita data

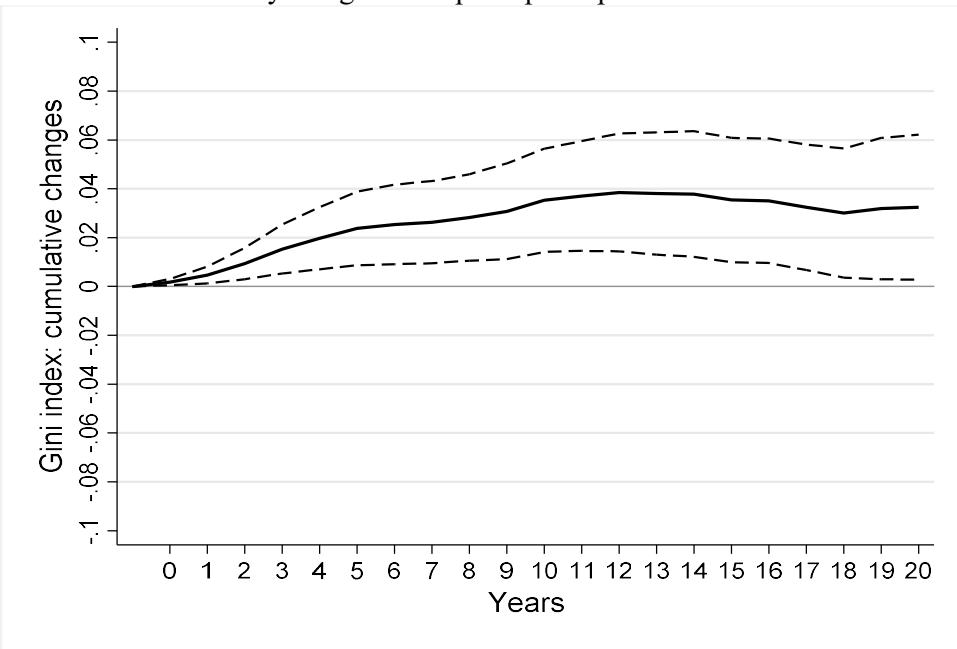
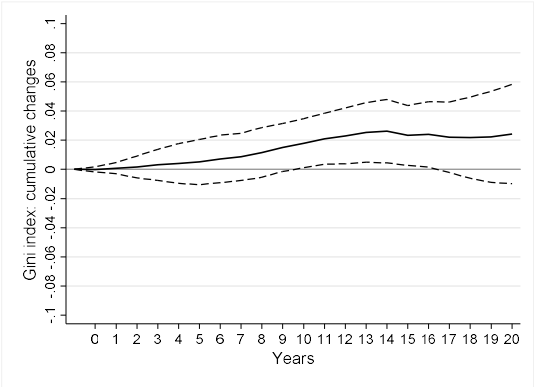
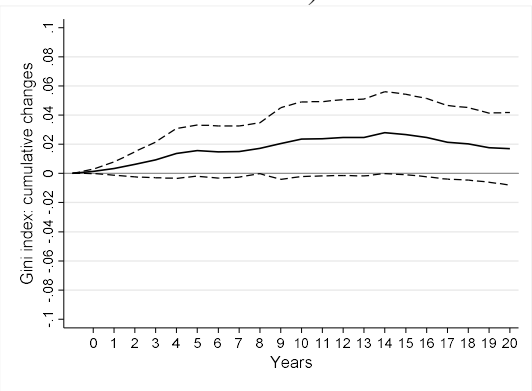


Figure A2. Cumulative change in Gini index of economic inequality as per income-category after economic disasters identified by using consumption per capita data

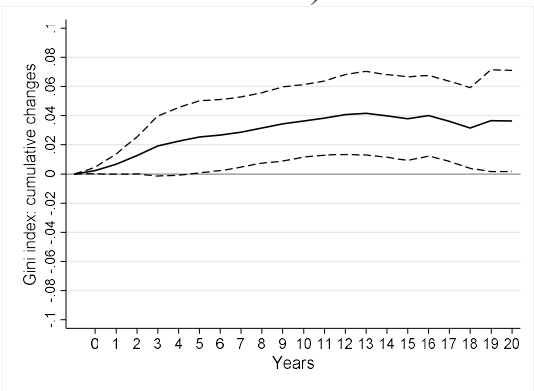
(a) Low income (6 countries, 30 disasters)



(b) Low-Middle Income (21 countries, 55 disasters)



(c) Upper-Middle Income (28 countries, 66 disasters)



(d) High Income (44 countries, 52 disasters)

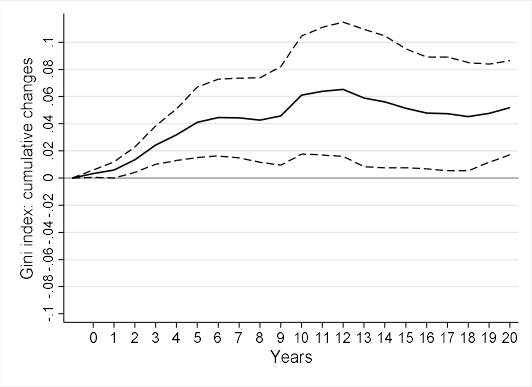
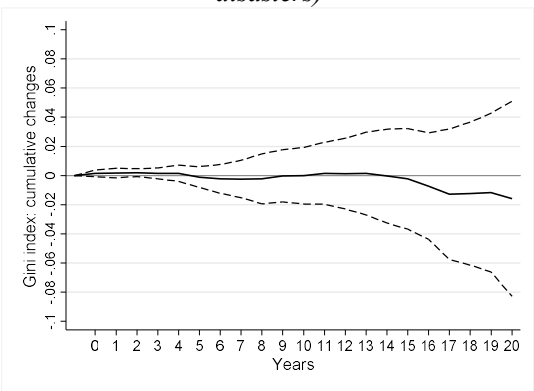
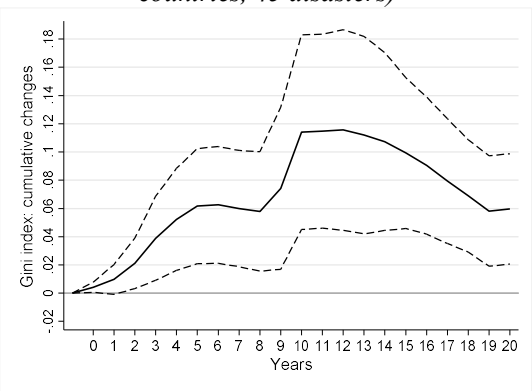


Figure A3. Cumulative change in Gini index of economic inequality as per region after economic disasters identified by using consumption per capita data

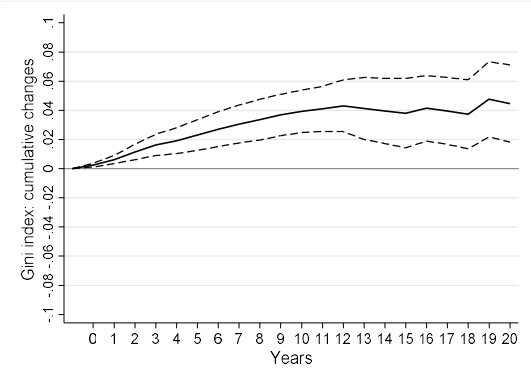
(a) East Asia and Pacific (14 countries, 16 disasters)



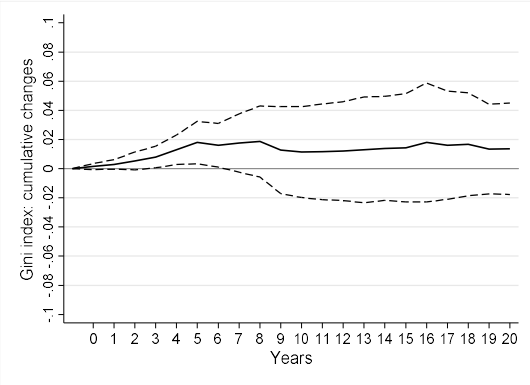
(b) Europe, Central Asia and North America (40 countries, 45 disasters)



(c) Latin America and Caribbean (18 countries, 51 disasters)



(d) Middle East and North Africa, and South Asia (11 countries, 18 disasters)



(e) Sub-Saharan Africa (16 countries, 73 disasters)