Growth and Inequality convergence: the role of environmentally related impacts on human capital

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Abstract

We examine inequality convergence over the past three decades and ask if environmentally related impacts of health (EIH) on human capital are responsible for the slow rate of inequality reduction in countries. Though higher initial incidence of EIH simultaneously worsens the rate of inequality reduction, we find that those countries that experience faster reduction in the level of EIH tend to converge to a lower level of inequality more quickly than their counterparts. Thus, estimates that exclude the incidence of EIH may bias the speed of convergence downward. We conclude that high rates of income growth, per se, do not reduce inequality within developing countries. Instead, the level of both initial inequality and EIH are just as important as growth. As such, policies targeted at reducing inequality must also address the health impacts from the environment.

Keywords: *Inequality, convergence, environmentally related impacts of health (EIH), income growth*

JEL: *D31, 015, Q51, Q52*

1 Introduction

A central tenet of the growth literature is the convergence hypothesis that per-capita income tends to grow more rapidly in poorer countries than in richer countries thereby converging in living standards (Bénabou, 1996). Countries that evolve toward the same level of per capita income should therefore also display similar income distribution. Thus, income convergence also implies inequality convergence, in that countries with high initial inequality will experience greater reductions in inequality compared to countries starting with low inequality.

Current evidence supports a tendency toward inequality convergence, while at the same time noting that inequality within countries has worsened considerably (Ravallion, 2003, 2018; Pande and Enevoldsen, 2021). Inequality convergence implies that countries starting with high initial inequality will experience greater reductions in inequality compared to countries starting with low inequality.[1] For example, Pande and Enevoldsen (2021) point out that the observed convergence in levels of per capita income across countries has occurred contemporaneously with rising within-country inequality, resulting in more of the world's poor living in middle-income countries and more inequality. Similarly, Ravallion (2018, p. 634) notes that "the two key features of how global inequality has been changing in the last few decades are the falling between-country component alongside a rising within-country component." If within-country inequality continues to rise, especially in low and middle-income countries, it could therefore become an important factor in preventing all countries from eventually displaying a similar income distribution.

The aim of this paper is to investigate whether there may be a second factor that could be influencing the speed of inequality convergence. This influence is due to environmentally related impacts on health (EIH), which are disproportionately affecting poorer as opposed to richer countries. If EIH are significant in low and middle-income countries, and increasingly affect the health outcomes of the poorest populations in these countries, then this could have an independent effect on changes in the distribution of income over time separate from the initial level of inequality. The intuition is that countries with higher incidence of EIH will have to be converging

[1] The inequality convergence hypothesis states that countries with similar structural parameters for technology, preferences and population growth will evolve toward a common per capita income, in a manner that reduces inequality in high inequality countries and increase inequality in low inequality countries (Ravallion, 2003).

at a very high speed in order to catch-up with the group. As a result, estimates that exclude this effect will underestimate the speed of convergence. Our aim here is explore further this possible relationship.

EIH refers to morbidity and mortality resulting from disease burden due to air pollution from solid fuels and ambient ozone, unsafe water and sanitation, soil and water pollution from chemicals or biological agents, anthropogenic climate change, and ecosystem degradation. The World Health Organization (WHO) estimates that more than half the world's population is exposed to unsafely managed water, inadequate sanitation and poor hygiene, resulting in about 827,000 deaths each year (WHO 2020). In 2019, pollution was responsible for approximately 9 million premature deaths, of which 90% occurred in low and middle-income countries (Fuller et al. 2022). Air pollution alone accounts for 7 million deaths, and about 3 billion people experience adverse morbidity risks from solid fuels or kerosene use for heating, cooking and lighting (WHO 2020). Particulate matter accounts for more than 4 million of such deaths each year, mainly in emerging market and developing economies (Nansai et al. 2021)[2]. In all, WHO estimates 13.7 million deaths, representing 24 percent of all global deaths, are linked to environmental factors each year (Prüss-Üstün et al. 2016). These exposures are highest in low and middle-income countries, which are plagued with the poorest health outcomes (WHO, 2020). As a result of EIH, health outcomes are getting better in richer countries but worse in poorer countries (Clark, 2011). As low-income and lower middle-income countries disproportionately suffer from EIH, these effects could constrain human capital accumulation and adversely impact growth, with consequences for inequality convergence.

Romer (1990) argues that human capital is essential in generating new ideas for the type of technological progress needed for growth, and by extension, higher living standards and inequality reduction. Countries with higher stocks of human capital experience rapid generation of research ideas and are better placed to absorb new products or ideas discovered elsewhere, and therefore tend to grow faster. Under this assumption, a poor country tends to grow faster than a richer

[2] In this paper we use the term emerging market and developing economies or just developing countries to refer to all low and middle-income countries. Also, high-income countries will be referred to as advanced economies. These income groupings are based on the World Bank's Country and Lending Groups classification (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519).

country through accumulating more human capital than what it has initially (Mankiw et al. 1992). By increasing the quantity of human capital per person, the rates of investment in both human and physical capital increases leading to higher per capita income (Barro, 1991). Implicit in these arguments is the assumption of a "healthy population" so that human capital will monotonically increase with training and education. However, the presence of attenuating factors such as EIH could depress human capital accumulation and reduce the quantity of human capital per person leading to lower income. While the effect of EIH may not be homogenous within a country, since it lowers the income of those who are disproportionately impacted, it consequently influences the distribution of income and lowers average income of the entire population (ie. per capita income). Clark (2011) found evidence in support of this argument that negative health outcomes (infant mortality) depresses per capita income in poor countries.

Since the variance of the income distribution is often taken to mean inequality, the effect of EIH on the distribution of income in the population directly influence inequality. This leads to one important hypothesis that countries with higher incidence of EIH will experience lower growth in mean income and less than a proportionate reduction in inequality overtime. In other words, EIH constrain the inequality-reducing impacts of economic growth, thus inhibiting the convergence of income inequality across countries. However, if those countries starting out with high incidence of EIH aggressively cut down the level of EIH, inequality could improve overtime leading to accelerated speed of inequality convergence. These possibilities have important implications for growth and inequality reduction in developing countries, who are disproportionately affected by EIH.

Investigating such a relationship is relevant to understanding the influence of the environment and growth on inequality reduction. The consensus in recent empirical analysis is that a higher growth rate will speed up absolute inequality reduction across countries, with some evidence that such reductions could be offset by high initial level of inequality (see, Ravallion 1997; Bénabou, 1996; Chen and Ravallion, 2001; Milanovic et al. 2011; Banerjee and Duflo 2003; Ravallion 1997, 2001, 2012). However, Ravallion (2003) found very little effect of initial inequality on the rate of inequality reduction. This raises the question whether the slow speed of inequality convergence is due directly to the effect of EIH. The intuition is that countries with higher incidence of EIH will have to be converging at a very high speed in order to catch-up with the group. As a result, estimates that exclude this effect will bias the speed of convergence downward. Alternatively, do EIH indirectly prevent improvements in income distribution by affecting the inequality-reducing impact of growth in per capita income?

To answer both questions, we follow a similar analytical approach to Ravallion (1997, 2012), who investigates the poverty-reducing impact of growth. We first examine the evidence for inequality convergence. Using the UNU-WIDER World Income Inequality Database (WIID) and employing the autoregressive technique, we find evidence of cross-country inequality convergence over the period of 1990-2019. Next, we test for inequality convergence while allowing for the influence of EIH defined as environmentally related disability adjusted life years (DALYs), which is the number of life years lost due to environmentally related mortality and morbidity. These data are from the Global Burden of Disease dataset available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool). We compute the incidence of EIH as the total number of environmentally related DALYs divided by the population. Our results suggest that, across 179 countries from 1990 to 2019, EIH offset the impact of growth in per capita income on inequality reduction, regardless of the measure of inequality adopted. Thus, the hypothesis that EIH have a significant influence on the inequality convergence process cannot be rejected.

More generally, our findings can be summarized as follows:

1) Higher (lower) initial incidence of EIH simultaneously worsens (improves) the rate of inequality reduction. Thus, those countries that experience faster reduction in the level of EIH tend to converge in inequality more quickly than their counterparts, *ceteris paribus*. The implication is that those countries starting out with high EIH would have to drastically cut the level of EIH overtime– thereby reducing inequality faster – to converge to the same low level of inequality as their counterparts. Thus, estimates that exclude the incidence EIH may bias the speed of convergence downward.

2) Since the 1990s, high inequality has co-existed with high growth rates in low and lower middle-income countries. The hypothesis that per capita income growth on its own improves inequality is largely rejected in the full sample of 179 countries over 1990-2019,

except for the period from 2000 to 2019, where the effect of growth on improving inequality is only significant at the 10% level.

3) For advanced countries, income growth and initial incidence of EIH have no significant effect on changes in inequality over 1990 to 2019. But in developing countries the relationships are less straightforward. Income growth on its own lowers the rate of inequality reduction, but when interacted with the initial incidence of EIH, the rate of inequality reduction increases.

The outline of the paper is as follows. Section 2 explores the trends in global inequality and environmental impacts on health (EIH). Section 3 provides the theoretical framework that link the incidence of EIH to inequality through the Lorenz curve. Section 4 provide the data and descriptive statistics while Section 5 details the empirical strategy and results. Section 6 concludes.

2 Patterns of Inequality and EIH

We begin by examining the key trends and patterns of inequality and environmental impacts on health (EIH) from 1990 to 2019. Over this period, the world economy has seen considerable growth in per capita income and living standards, which has had significant impacts on global inequality. Since the mid-1990s, environmentally related deaths and morbidity (DALYs) globally have also declined significantly, although the level of EHI in emerging market and developing countries remain substantially higher than those found in advanced economies.

2.1 Inequality convergence

Figure 1 plots the annualized log change in Gini index from 1990 to 2019 against the levels in 1990 for 172 countries.[3] A negative annualized growth in Gini index implies a reduction of inequality and a positive growth rate implies a worsening of inequality. The straight lines in Figure 1 indicate the fitted regressions lines for each income group of countries: low, lower middle, upper

[3] To smooth the graph in figure 1, we drop 7 outliers including Azerbaijan, Bulgaria, Romania, Latvia, Sao Tome and Principe, Luxembourg and Uzbekistan.

middle and high income. While the regression line of the low-income group has a slope of -1.28 with a t-score of -3.09, that of the lower middle-income group has a slope of -0.52 with a t-score of -2.44, the upper middle-income group has a slope of -1.15 with a t-score of -5.56, and the high-income group has a slope of -0.70 with a t-score of -4.44, which indicates strong evidence of within-income group convergence over 1990-2019.[4]

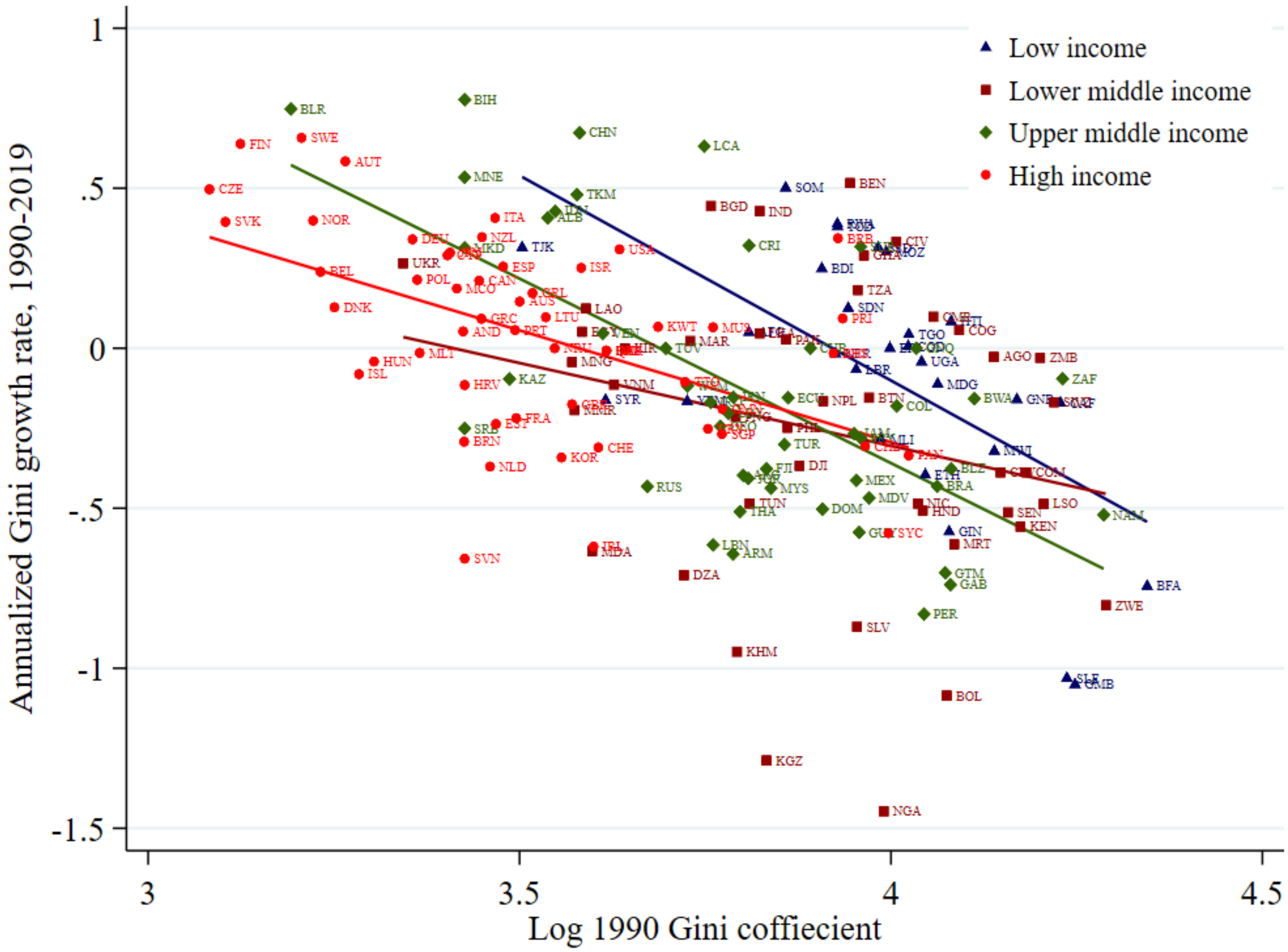

Figure 1: Inequality Convergence: Growth in inequality plotted against initial inequality

Source: Authors' calculation based on data from UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidglobal). Version 31 May 2021.

As indicated by the much steeper slope of the regression line, the low-income group of 28 countries has the highest rate of inequality reduction ranging from -1.1% to 0.5%. This is followed by the

[4] The estimates of the slope and t-score of the regression lines in Figure 1 are obtained by regressing the log Gini index in 1990 on the annualized growth in inequality. Standard errors are robust to heteroskedasticity (White). The range of annualized reduction in inequality in each of the income group is obtained from the summary statistic at the group level.

high-income group of 47 countries, which have an annualized reduction in inequality ranging from -0.83% to 0.77%. The lower middle-income group of 43 countries has an annualized rate of inequality reduction, ranging from -1.45 to 0.52 with large dispersions among countries.

In sum, while income inequality has been falling globally, the proportionate rate of decline is slower among lower middle-income countries compared to the other income groups. This outcome is concerning, given that more of the world's poor are living in middle-income countries (Pande and Enevoldsen 2021) and that the income of those at the bottom of the global distribution of income has remained fairly stagnate in recent decades (Gradín 2021). As we shall see next, this stagnation in the distribution of income and the slower rate of inequality reduction among lower middle-income countries seem to have coincided with declining but high levels of EIH in all developing countries.

2.2 Global Gini index and EIH

Figure 2 compares the trends from 1990 to 2019 in the global Gini index and EIH as measured by environmentally related disability-adjusted life years (DALYs). Over this period, the global Gini index fell from about 70 to 60, indicating a gradual lessening of inequality. This trend seems to have coincided with a rapid decline in environmentally related DALYs globally, which fell from about 553 million in 1990 to 362 million in 2019 representing about a 35 percent reduction (see Figure 2). Over this period, world environmentally related deaths fell by just 8 percent; from about 12 million to 11million (see Appendix Figure A1).[5] At the same time, we observe a significant shrinking of the tail of the Kernel distribution of environmentally related DALYs in 2019, compared to the elongated and flatter distribution in 1990 (see Appendix Figure A2).

[5] The actual estimates of total environmentally related DALYs in Figures 2 and 3 and total environmentally related deaths in Appendix Figure A1 could be larger since the available data only cover unsafe water, sanitation, handwashing, air pollution including particulate matter pollution, ambient particulate matter pollution, household air pollution from solid fuels, and ambient ozone pollution as well as suboptimal temperature (both low and high temperature) and other environmental risks associated with residential radon and lead exposure.

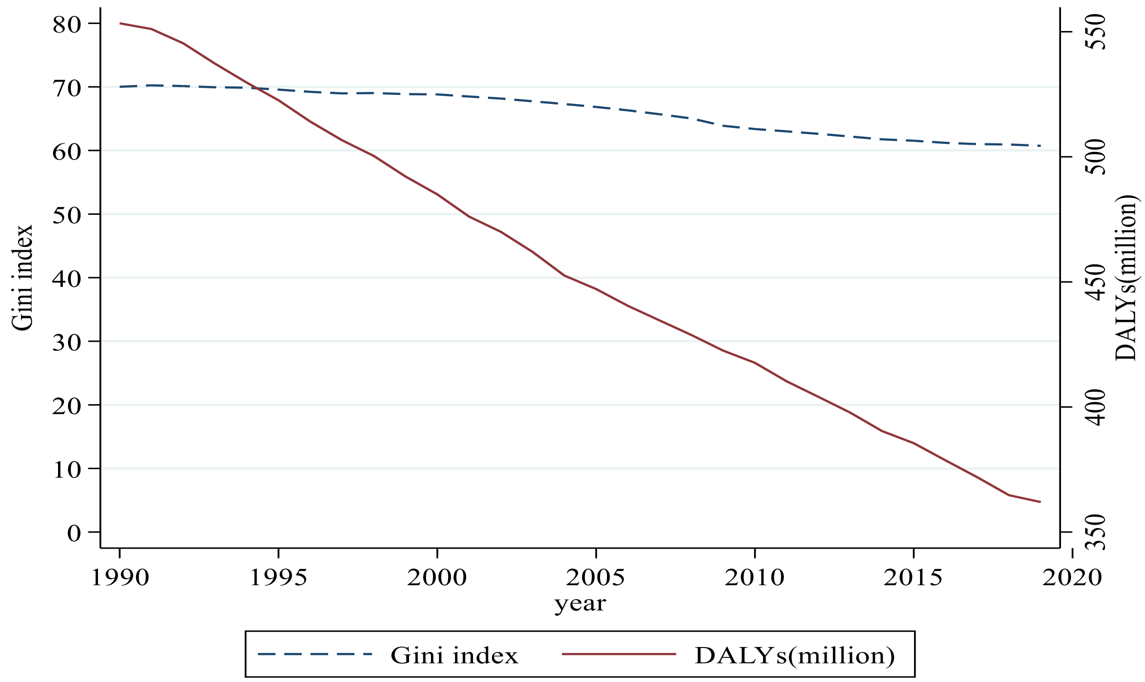

Figure 2: World Gini coefficient and environmentally related DALYs

Note: Environmentally related disability adjusted life years (DALYs) are the number of life years lost due to environmentally related mortality and morbidity. These environmental impacts on health include disease burden due to air pollution from solid fuels and ambient ozone, unsafe water and sanitation, soil and water pollution from chemicals or biological agents, anthropogenic climate change, and ecosystem degradation. See Appendix Figure A1 for similar graph for environmentally related deaths. That is the actual number of people who died due to environmental causes.

Source: Authors calculation based on data from UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidglobal). Version 31 May 2021.
Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

2.3 Heterogeneity of EIH across income groups

EIH vary considerably among countries over 1990 to 2019. As noted in the introduction, these health risks disproportionately impact the poorest and most vulnerable people in emerging market and developing economies. As Figure 3 shows, environmentally related DALYs are substantially higher in low and middle-income countries than in advanced economies. However, slopes of the curves suggest that these lower middle-income countries are reducing environmentally related DALYs much faster than high-income countries.

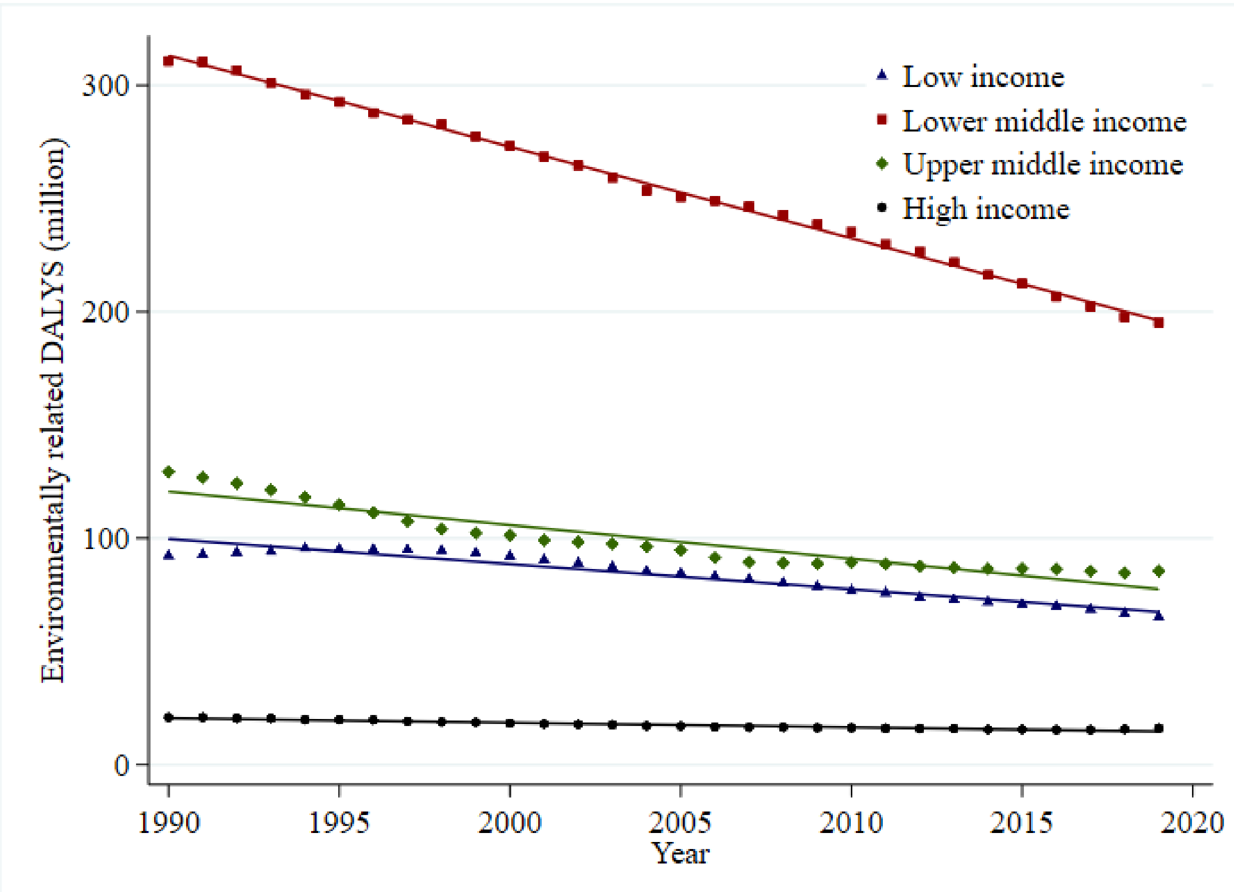

Figure 3: Environmentally related DALYs by income groups

Source: Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

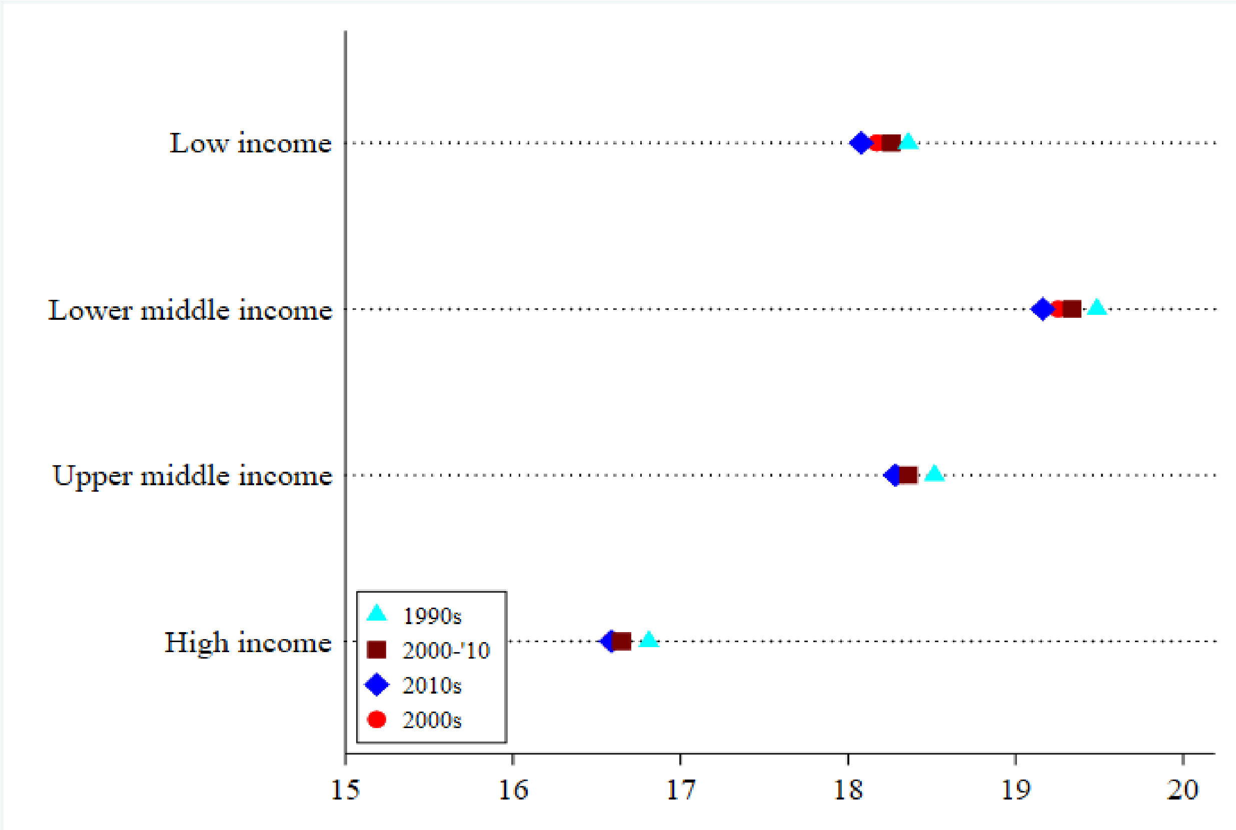

Figure 4: Decadal average of log of environmentally related DALYS by income groups

Source: Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

Figure 4 presents the decadal average in the level of EIH among countries based on income classification. Environmentally related DALYs are lowest in the high-income countries compared to the other income groups, with lower middle-income countries displaying the highest levels of EIH in terms of decadal averages. However, environmentally related DALYs are considerably different across income groups. While low and lower middle-income countries are predominantly impacted by risks from unsafe water, sanitation, handwashing and household air pollution from solid fuels, middle-income countries are predominately impacted by particulate matter pollution and other forms of air pollution, which may be attributed to the rapid industrialization and urbanization experienced by such countries (see GBD, 2019).[6]

[6] Note: Values plotted in Figure 3 and 4 are the total estimated sum of all environmentally related mortality and morbidity for each of the income groups as of 2019 (see GBD 2019).

2.4 EIH convergence

To form a comparable index across countries, we derive the incidence of EIH as the total number of environmentally related DALYs divided by the population of the country.[7] Though the incidence of EIH is substantially high among low and lower-middle income countries, Figure 5 shows that these developing countries are reducing the level of EIH faster than the advanced countries. Thus, the evidence in Figure 5 could be loosely describe as “convergence in EIH”.

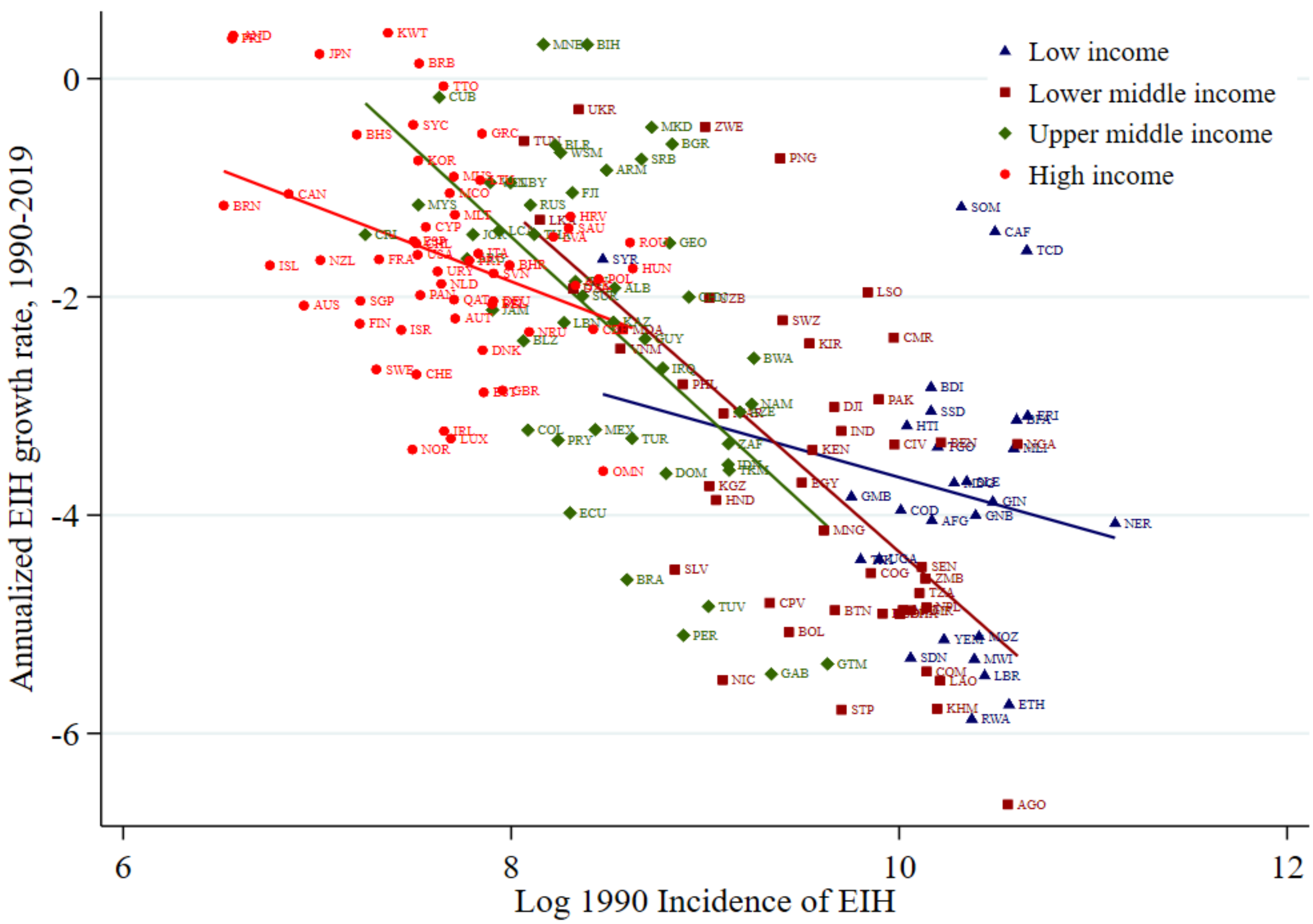

Figure 5: Growth in incidence of EIH plotted against initial levels of EIH

Source: Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

[7] To avoid negative values from taking log, we multiply the incidence by 100,000. This allows us to interpret the resulting incidence as a portion of every 100,000 life years in the population lost due to environmentally related DALYs.

The estimated regression line of the lower middle-income group has a slope of -1.56 with a t-score of -6.13, the upper middle-income group has a slope of -1.63 with a t-score of -5.48, and the high-income group has a slope of -0.68 with a t-score of -2.94, and the low-income group has a slope of -0.5 that is not significant at the 5% significant level. Although the incidence of EIH is still high in developing countries, their rate of EIH reduction over 1990-2019 is much higher than that of the advanced countries.

This outcome is supported by evidence that the health hazards associated with unsafe water, sanitation, hand washing and household air pollution from solid fuels – which make up the bulk of environmentally related deaths and DALYs in developing countries – have been decreasing in recent decades (see GBD 2019). Such a reduction in EIHs in developing countries could also have an impact on inequality, as the portion of income inequality attributable to the effect of EIH on the income distribution within developing countries should also fall. We theoretically demonstrate this relationship in the following section.

3 The Lorenz Curve and EIH

As discussed in the introduction, the presence of EIH reduces the amount of human capital per person and thereby influences the distribution of income in the population. The dispersion or variance of the income distributions is often taken to mean income inequality. To illustrate the potential impact of EIH on inequality, we explore its effect on average income and the properties of Lorenz curve. Since inequality is the variance of income distribution, countries that are disproportionately affected by EIH will have highly skewed income distributions with large variances in income. Though the effect of EIH may not be homogenous within a country, it consequently lowers the income of those who are disproportionately impacted, thereby lowering the average income of the entire population and thus causing the Lorenz curve to display a greater disparity in income.

We adopt the theoretical framework developed by Barbier and Hochard (2018) and Gastwirth (1971), to illustrate the impact of EIH on inequality. Let σ be the incidence of EIH, which is the total number of environmentally related DALYs divided by the population. Given this incidence, let the proportion p of the population that receives income less than some level y be defined by the cumulative distribution function, $p=\int_0^y f(t,\sigma)\,dt=F(y,\sigma)$. Following Gastwirth (1971), the inverse of the cumulative distribution function $F^{-1}(p,\sigma)=y(p,\sigma)$ defines the quantile function for p; i.e., the income level y below which we find a proportion p of the population. This leads directly to the derivation of the Lorenz curve, a plot of the fraction of total income that the holders of lowest p^{th} portion of income possess, given the effects of EIH on the distribution of income.

Under these assumptions, the Lorenz curve associated with any random income y with a finite population mean income $\mu=\int_0^\infty y\,dF(y)=\int_0^\infty yf(y)\,dy$ is defined as

$$L(p)=\frac{1}{\mu}\int_0^p F^{-1}(t)\,dt \quad , \quad L_p=\frac{\partial L}{\partial p}=\frac{y(p,\sigma)}{\mu}>0\ , \quad L_{pp}>0\ , \quad 0\leq p\leqslant 1, \tag{1}$$

where $L(p)$ is the fraction of total income that the holders of the lowest p^{th} fraction of income possess. As $y'(p)>0$, the Lorenz curve is an increasing and convex function of p. Consequently, the derivative of the Lorenz curve with respect to p gives the ratio of the income of that share of the population to the average income of the entire population. However, in this case, the level of inequality is also a function of σ.

Let g be the resulting inequality index, i.e., the share of the population with income level no higher than some threshold amount $z(\sigma)$, which based on the above arguments is influenced by σ. That is $g=F(z(\sigma))$ and thus $z(\sigma)=F^{-1}(g)$. Inverting the latter function, evaluating it at $p=g$ and replacing $y(p,\sigma)$ with $z(\sigma)$, we obtain

$$g=L_p^{-1}\left(\frac{z(\sigma)}{\mu}\right), \quad \frac{\partial g}{\partial \sigma}>0. \tag{2}$$

Equation (2) indicates that the level of inequality depends on the mean income of the population, and the incidence of EIH, as well as the properties of the Lorenz curve. We expect that a marginal increase in σ will increase the level of inequality and a decrease in σ will reduce inequality. This *direct effect* of the incidence of EIH on inequality is an empirically testable hypothesis. In addition, as σ may also influence mean income, it could *indirectly* affect the inequality-reducing impacts of income growth. Our hypothesis is that a higher incidence of EIH is associated with a weaker inequality-reducing impact of growth in average income.

The above lead us to two testable hypotheses as to whether or not the incidence of EIH: (1) directly influences the rate of inequality reduction and convergence, and (2) impedes the inequality-reducing impact of growth in mean income. The key variables required to test empirically these hypotheses include measures of inequality, mean income and incidence of EIH.

4 Data and Descriptive Statistics

We construct a measure of EIH for 179 countries spanning 1990 to 2019 from the Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool). The incidence of EIH (σ) is the proportion of the population exposed to environmentally related disability adjusted life years (DALYs), which is the number of life years lost due to environmentally related mortality and morbidity. Specifically, we obtain the incidence of EIH by dividing the total number of environmentally related DALYs by the population. As shown in Table 1, environmentally related DALYs alone accounts for 14,046 out of every 100,000 life years lost in low and lower middle-income countries.

Our principal measure of inequality (g) is the Gini index. However, when comparing country inequality, we are also interested in isolating within-country component of inequality. Such decompositions are not generally possible with the Gini index, which is based on the absolute difference of all random pairs of incomes normalized by the mean. Therefore, we consider indices from the Generalized Entropy family including GE(0) or Mean-log deviation (MLD), GE(-1) and GE(1) as a robustness check.[8]

[8] GE represent Generalized Entropy. Ordinarily, GE (0) is equivalent to Mean-log deviation (MLD), which is a relative inequality measure like the Gini index in that they both depend on the ratio of incomes to the mean (Gradín 2021)

Table 1: Descriptive Statistics of Key variables for 179 countries from 1990-2019

Variable	Low-and lower income	Upper-middle income	High income	All 179 countries	
	Mean	Mean	Mean	Mean	Standard Deviation
Per capita GDP	3,547	11,720	37,048	16,452	18,088
Gini index	50.87	45.31	35.34	44.40	11.13
Generalized Entropy family index (GE(-1))	123.8	85.45	37.26	85.76	102.4
Mean-log deviation (MLD) or GE(0)	51.23	40.26	23.51	39.40	22.46
Generalized Entropy family index (GE(1))	52.89	40.23	23.17	39.96	22.46
Bottom 40%, share of the total	12.00	14.09	18.77	14.73	5.006
Environmentally related DALYs (100000)	14,046	4,031	1,796	7,404	8,616
1990 Gini index	52.18	45.52	34.17	44.62	12.55
1990 GE(-1)	173.0	73.26	34.04	101.5	153.7
1990 GE(1)	56.47	41.71	21.74	41.37	25.86
1990 GE(0)	56.81	40.30	22.14	41.25	27.46
1990 Environmentally related DALYs (100000)	21,819	6,169	2,294	11,317	12,068
Annualized Gini growth rate (%)	-0.162	-0.140	0.102	-0.072	0.494
Annualized GE (-1) growth rate (%)	-0.589	-0.0237	0.318	-0.146	2.663
Annualized GE (1) growth rate (%)	-0.364	-0.359	0.245	-0.169	1.086
Annualized GE (0) growth rate (%)	-0.414	-0.230	0.240	-0.156	1.270
Annualized income growth rate (%)	1.567	2.170	1.868	1.828	1.706

Note: Based on a sample 179 countries in total: 56 are high-income countries, 49 upper -middle-income countries, 45 lower middle-income countries and 29 low-income countries for which data on environmentally related deaths and DALYs are available. See Appendix Table A4 for list of countries. Annualized growth rates are calculated as the change in the log of the variable of interest between 1990 and 2019 divided by time interval of 29 years and expressed as 100%.

Source: Authors calculation based on data from UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidglobal). Version 31 May 2021.
Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

While the Gini index is less sensitive to the two extremes of the income distribution, MLD is particularly sensitive to the bottom 40 percent of the distribution, GE (-1) show extreme sensitivity to the very bottom of the income distribution and the Theil, GE(1) is sensitive to the top of the distribution. Naturally, all the inequality indices are high in low- and lower middle-income countries compare to the sample average (see Table 1). The statistics of the GE (-1) shows that inequality is much higher in low-and lower-middle income countries than the levels reveal by the Gini index. Thus, depending on the distributive sensitivities under focus, the conclusions about the weight of inequality decline shown in figure 2 maybe contentious. However, by comparing the initial inequality values of all indices and the average over 1990-2019, one thing that is less contentious is the fact that all indices agree that inequality has being slowly declining since the 1990s. See Gradín (2021) for a detailed discussion of these trends in inequality.

The mean income (μ) is captured by per capita gross domestic product (GDP) constant in 2017 US$. The data on inequality variables and per capita GDP are obtained from the most recent version of the UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidglobal) Version 31 May 2021, (available online at https://doi.org/10.35188/UNU-WIDER/WIIDcomp-310521). The WIID Companion dataset could be describe as the gold standard for inequality indices with broad-ranging indices including the Gini coefficient and indices from the General Entropy family. This dataset produces internationally comparable country level data on a variety of inequality measures and income distribution estimates based on standardized publicly sourced data for 209 countries and territories covering the period of 1950 to 2019. This allows us to test our hypothesis over a broader range of inequality indices.

5 Empirical Strategy and Results

As summarized in Durlauf et al. (2005), there are many different econometric specifications for empirically measuring convergence. We follow the standard approach, which is also used by Ravallion (2012) for poverty convergence, to test for inequality convergence and the effect of EIH on the speed of convergence and inequality reduction. This involves several cross-sectional analyses using the ordinary least square (OLS) estimator over intervals of 10 or more years, which we will discuss below. While the cross-sectional regression is not without limitations, it captures cross-country variations well and avoids the temporary noise and trends in the data that maybe transitory and do not influence long-run parameters of interest (Kremer et al. 2022).

While testing for poverty convergence, Ravallion (2012) specifies a homogeneity restriction for a direct and indirect effect of income growth on poverty reduction; we follow similar strategy to test the direct and indirect effects of income growth on inequality reduction. The aim of the homogeneity restriction is to be able to estimate the growth elasticity of inequality reduction conditional on initial incidence of EIH. While our empirical strategy follows closely with the strategy in Ravallion (2012), it is important to note that there is a significant conceptual difference between our hypothesis and that of Ravallion (2012). For one, Ravallion (2012) specifies a regression indicating that the change in poverty over time could be influence by the initial level of poverty. As a robustness check, he also examines whether the initial level of inequality could inhibit the poverty-reducing impact of growth. In comparison, our empirical strategy investigates whether the change in inequality over time could be influenced by the initial level of inequality as well as the initial incidence of EIH, or alternatively, whether the initial incidence of EIH could also inhibit the inequality-reducing impact of growth. The following sub-sections outline in more detail the steps of our approach.

5.1 Effect of EIH on inequality reduction and convergence in inequality

Our first step is to examine whether income inequality is converging across countries over 1990 to 2019. The standard inequality convergence hypothesis in the literature is that changes in inequality over time will be influenced by the level of initial inequality, which is commonly express as:

$$\gamma\left(g_{it}\right) = \lambda_0 + \lambda_1 \ln\left(g_{it-\tau}\right) + \varepsilon_{it} \tag{3}$$

where i is each country's observation, t is the present year of data, τ is the length of year interval in each cross-section of data and ε_{it} is the disturbance term. The dependent variable in (3) is

$$\gamma\left(g_{it}\right) \equiv \ln\left(\frac{g_{it}}{g_{it-\tau}}\right) \Big/ \tau,$$

which is the annualized change in the log of inequality index and thus represent the growth in inequality and depending on the sign could also be called the rate of inequality reduction. A negative $\gamma\left(g_{it}\right)$ implies that inequality index for the current year is lower than the previous year and the reverse is true for positive values. As such, increases in $\gamma\left(g_{it}\right)$ is a sign of worsening inequality. The underling null hypothesis (H_0) for equation (3) is that there is no evidence of inequality convergence or that the initial level of inequality does not affect the rate of change in inequality, i.e. $\lambda_1 = 0$.

Our second hypothesis is that inequality may be declining over time, but it may be doing so at a slower rate due to the presence of EIH. If that holds true, then including the initial incidence of EIH as a regressor in (3) should lower the annualized rate of reduction in inequality. All else being equal, countries with a higher initial level of EIH incidence should experience less inequality reduction than countries with a lower initial level. More importantly, we also what to examine the effect of initial incidence of EIH on the convergence parameter, λ_1, which is formally expressed in equation (2) as $\frac{\partial g}{\partial \sigma} > 0$. The hypothesis is that the inclusion of initial incidence of EIH will increase the effect of the initial inequality.

Thus, in our second step, we respecify (3) to include initial incidence of EIH as follow

$$\gamma\left(g_{it}\right) = \lambda_0 + \lambda_1 \ln\left(g_{it-\tau}\right) + \lambda_2 \ln\left(\sigma_{it-\tau}\right) + \varepsilon_{it}. \tag{4}$$

Equation (4) specifies that the rate of change in inequality is influenced by the initial level of inequality and the initial incidence of EIH. Thus, the direct effect of incidence of EIH on the rate of inequality reduction will be verified if the null hypothesis of $\lambda_2 = 0$ is rejected. If $\lambda_2 > 0$, then countries starting out with higher initial incidence of EIH will be reducing inequality more slowly than countries with a lower initial incidence.

Consequently, we estimate (3) and (4) and test the corresponding two hypotheses for the direct effects of initial inequality $\ln(g_{it-\tau})$ and initial incidence of EIH $\ln(\sigma_{it-\tau})$ on the annualized change in inequality. Our main results for regressions (3) and (4) using the OLS estimator are summarized in Table 2. Columns 1 and 2 report the regressions for the 179 countries over 1990-2019, columns 3 and 4 are for the 20-year period from 1990 to 2010, and the remaining columns are for the periods 1990-2000, 2000-2019 and 2000-2010.

In all 5 samples, the estimated annual convergence rate for the Gini index ranges from 0.5% to 1.7% not conditional on any other explanatory variable. These estimates were revised upward to a range of 0.8% to 2% when we include the initial incidence of EIH. The corresponding estimates of this convergence parameter in Ravallion (2003) and Bénabou, (1996) are much lower, less than -0.06% and 0.91% respectively. Such variation in estimates could be the result of the differences in the sample of countries and years in our empirical analysis compared to the earlier studies. While Ravallion (2003) and Bénabou, (1996) use the Deininger and Squire (1995) dataset and others to compile a sample of 21 to 69 countries, our sample consists of 179 countries, which includes a much larger number of low and lower middle-income countries compared to the earlier studies. In addition, our analysis covers a much later period from 1990 to 2019.

Table 2: Estimates of the effects of initial inequality and incidence of EIH on inequality reduction, 1990-2019

Variable	1990-2019		1990-2010		1990-2000		2000-2019		2000-2010	
Constant	3.10† [0.417]	3.04† [0.395]	4.38† [0.502]	4.31† [0.474]	6.73† [0.900]	6.67† [0.875]	1.73† [0.563]	1.77† [0.553]	2.82† [0.773]	2.87† [0.754]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-0.84† [0.109]	-1.06† [0.142]	-1.17† [0.131]	-1.39† [0.168]	-1.75† [0.234]	-1.97† [0.284]				
Log of Gini index, initial year 2000, $\ln(g_{it-\tau})$							-0.51† [0.148]	-0.78† [0.194]	-0.80† [0.204]	-1.16† [0.253]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.10† [0.036]		0.10** [0.041]		0.10 [0.062]				
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$								0.12** [0.045]		0.15† [0.057]
Observations	178	178	178	178	178	178	179	179	179	179
R-squared	0.249	0.282	0.312	0.335	0.287	0.297	0.052	0.087	0.068	0.102

Note: The dependent variable is the annualized change in the log Gini index. The estimates are for 179 countries for which EIH is available. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.[9]

[9] The lists of control variables we considered include GDP per capita, the income share of the bottom 40%, and other inequality indices such as GE (-1) and GE (0). While the inclusion of the control variables significantly improves the R-Square, they did not significantly improve the coefficient on our variable of interest, ln $\sigma_{it-\tau}$. For example, when we estimate equation 4 and included the income share of the bottom 40% as a control, λ_1 increase from the -1.06 reported in column 2 of Table 2 to -2.71 with a t-score of -20.84 but λ_2 fell from 0.1 to 0.009 and is statistically insignificant even at the 10% level. λ_2 did not improve even when we include GDP per capita and GE (-1). Meanwhile, the coefficient on the income share of the bottom 40% is -1.84 and statistically significant at the 5% level. This should be expected since the annualized Gini growth rate which is our dependent variable is a derivative of the income distribution. It makes intuitive sense that our list of controls will be strong predictors of the dependent variable. However, their strong effect on the dependent variable diminishes or cancel out the effect of EIH. Therefore, to isolate the effect of EIH on the rate of inequality reduction and convergence – which is the core aim of this paper – the estimates reported throughout the paper are without these controls.

The null hypothesis that $\lambda_2 = 0$ is also rejected, as this parameter is positive and significant at the 1% or 5% level in all samples except in 1990-2000 (see Table 2). The associated elasticity is positive and ranges from 0.1 to 0.16, suggesting that a 10 percent reduction in the initial incidence of EIH would improve the change in Gini index by 1.0 to 1.6 percent. It should also be noted that inclusion of initial incidence of EIH does not diminish the effect of initial inequality on inequality reduction over time, instead the convergence parameter improves. As indicated in Table 2, when initial EIH incidence is included with initial inequality, in all regressions, λ_1 is more negative and significant at the 1% level.

Finally, perform a two-stage instrumental variable (IVE) regression of equation (4) which captures the endogeneity between initial inequality and initial incidence of EIH (see Appendix Tables A1). While the results corroborate our earlier findings of inequality convergence, the convergence parameters and λ_2 in the IVE model are generally larger than the estimates from the OLS model. These large differences between the OLS and IVE estimates could be attributed to measurement error or weak instrument problem. Thus, the OLS estimates are more preferred because the convergence parameter estimates are unbiased, consistent and low enough to generate convergence toward a medium inequality.

In conclusion, our estimations of equations (3) and (4) suggest that, over 1990 to 2019, there are strong evidence of inequality convergence, and high initial incidence of EIH worsens the annualized rate of inequality reduction over time. In fact, our estimations suggest that both effects are present simultaneously, and the convergence parameter is more negative as a result. This result corroborates our theoretical framework. Incidence of EIH and Gini index complements each other, in that a high initial incidence of EIH implies that the component of income inequality attributable to EIH are high. As such, the average initial inequality is also high, which is why λ_1 is larger or more negative upon the inclusion of initial incidence of EIH. Thus, the estimates that exclude EIH bias the speed of convergence downward. However, before exploring these implications further, next we examine the possibility that initial EIH may indirectly impact changes in inequality by affecting the inequality-reducing influence of growth in per capita income.

5.2 EIH and the inequality-reducing impact of income growth

We have seen that direct impact of EIH on changes in inequality over time cannot be rejected; that is, countries starting with a higher initial incidence of EIH will have a lower rate of inequality reduction compared to countries with a lower initial incidence. Next, we examine whether the presence of EIH hinders the inequality-reducing impact of income growth. To do this, we respecify (4) to include a direct effect of income growth and an interaction term between income growth and initial incidence of EIH. This leads to the following model specification

$$\gamma\left(g_{it}\right) = \lambda_0 + \lambda_1 \ln\left(g_{it-\tau}\right) + \lambda_2 \ln\left(\sigma_{it-\tau}\right) + \left(\beta_0 + \beta_1 \sigma_{it-\tau}\right)\gamma\left(\mu_{it}\right) + \lambda_3 Z_{it} + \varepsilon_{it} \qquad (5)$$

where $\gamma(\mu_{it}) \equiv \ln\left(\mu_{it}/\mu_{it-\tau}\right)/\tau$ is the annualized change in the log of mean income and thus represent the growth in per capita income, and Z_{it} is a vector of control variables. In addition to testing for the null hypotheses $\lambda_1 = \lambda_2 = 0$, the key restriction here is the homogeneity restriction that tests the null hypothesis $\beta_0 + \beta_1 = 0$. Failure to reject the null hypothesis of homogeneity, i.e., $\beta_0 = -\beta_1$, confirms that initial incidence of EIH have an indirect influence through 'adjusting' the growth elasticity of inequality reduction. As such the inequality-reducing impact of income growth in (5) can be specified as $\beta\left(1 - \sigma_{it-\tau}\right)\gamma\left(\mu_t\right)$.[10] Thus, as the initial incidence of EIH increases (decreases), the rate of inequality reduction becomes less (more) responsive to growth in per capita income and reaches zero (one) at a sufficiently high (low) incidence of EIH.

Table (3) depicts the various regressions of equation (5) for 179 countries over various periods from 1990 to 2019. As before, we can resoundingly reject the null hypothesis that $\lambda_1 = \lambda_2 = 0$ at the 1% or 5% significant level in all samples except in 1990-2000. In addition, in all sample periods, the null hypothesis $\beta_0 = 0$ cannot be rejected except at the 10% significance level over

[10] In the case that $\lambda_1 = \lambda_2 = \lambda_3 = 0$ and $\beta_0 + \beta_1 = 0$ both hold, then the regression in (5) further resolves to $\gamma\left(g_{it}\right) = \lambda_0 + \beta\left(1 - \sigma_{it-\tau}\right)\gamma\left(\mu_{it}\right) + \varepsilon_{it}$, $\beta < 0$. The inclusion of control variables to estimate λ_3 did not significantly improve our variable of interest, $\ln\sigma_{it-\tau}$. As in Table 2, inclusion of the income share of the bottom 40% as a control significantly improve λ_1 from the -1.1 reported in column 1 of Table 3 to -2.7 with a t-score of -21.01 but λ_2 fell from 0.1 to 0.02 and is statistically insignificant even at the 10% level. λ_2 did not improve when we include GDP per capita and GE (-1). Meanwhile, the coefficients on the income share of the bottom 40% (ie -1.82) and annualized income growth rate (0.03) are both statistically significant at the 5% level.

2000-2019. These results indicate that income growth does not influence changes in inequality at the 5% significant level for the 179 countries over 1990 to 2019, and correspondingly, there is no indirect impact of initial EIH on the inequality-reducing impacts of growth.

Table 3: The effects of Gini index, incidence of EIH and income growth on changes in inequality

Variable	1990-2019		1990-2010		1990-2000		2000-2019		2000-2010	
Constant	3.00†	-0.13†	4.18†	-0.08	6.77†	0.18**	2.29†	-0.13**	3.62†	-0.10
	[0.384]	[0.047]	[0.475]	[0.058]	[0.884]	[0.082]	[0.540]	[0.057]	[0.763]	[0.120]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-1.1† [0.142]		-1.4† [0.169]		-1.9† [0.286]					
Log of Gini index, initial year 2000, $\ln(g_{it-\tau})$							-0.87† [0.177]		-1.31† [0.229]	
Log incidence of EIH initial year 1990, $\ln(\sigma_{it-\tau})$	0.10** [0.041]		0.11** [0.048]		0.08 [0.069]					
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$							0.11** [0.047]		0.15** [0.063]	
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$	0.01 [0.024]		0.03 [0.027]		-0.02 [0.025]		-0.07* [0.038]		-0.09 [0.064]	
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$	0.00 [0.00]		-0.00 [0.00]		0.00 [0.00]					
Growth rate interacted with incidence of EIH in 2000, $\gamma(\mu_{it})\sigma_{it-\tau}$							0.00 [0.00]		0.00 [0.00]	
EIH-adjusted growth rate, $\gamma(\mu_{it})(1-\sigma_{it-\tau})$		0.03* [0.020]		0.04* [0.022]		-0.01 [0.020]		-0.03 [0.031]		-0.04 [0.054]
Homogeneity test: Wald test statistics, $\beta_0 + \beta_1 = 0$	0.17		0.88		0.81		3.54*		1.91	
Observations	178	178	178	178	178	178	179	178	179	178
R-squared	0.283	0.010	0.340	0.014	0.301	0.002	0.122	0.010	0.143	0.010

Note: The dependent variable is the annualized change in the log Gini index. The estimates are for 179 countries for which EIH is available. The β coefficient of the restricted model reported in column 5 did not improve with inclusion of control variables such as include GDP per capita, the income share of the bottom 40%, and other inequality indices such as GE (-1) and GE (0). Heteroskedasticity-consistent robust standard errors (White) in parentheses. † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The regressions also indicate that we can accept the homogeneity restriction $\beta_0 + \beta_1 = 0$ in all the samples except the sample of 2000-2019. However, the corresponding β coefficients from the restricted model reported in column 2,4,6 and 10, in Table 3, are not statistically significant at the 5% level even when we include control variables. However, at the 10% significant level we found a positive growth elasticity of inequality reduction conditional on initial incidence of EIH.

Unlike the positive poverty-reducing impact of growth found in Ravallion (2012) and Barbier and Hochard (2018), we found that the effect of initial incidence of EIH outweighs the inequality-reducing impact of income growth in the full sample at the 10% significant level. This is because the impact of growth on rate of inequality reduction is zero. This latter result is consistent with Ravallion (2014), who posit that there maybe a trade-off between reducing inequality and reducing poverty and that higher growth has not improved inequality within countries but rather that decreasing global inequality is due to falling inequality between countries.

We also estimate equations (4) and (5) over 1990-2019 for the four major income groups: low-income, lower middle-income, upper middle-income and high-income countries. Table 4 depicts the results. Like the cross-country estimates for the full sample reported in Tables 2 and 3, in all estimations across income groups, initial inequality has a negative and significant impact on changes in inequality over time. That is, a higher initial level of inequality in 1990 leads to more inequality reduction over 1990-2019 in all four income group samples. The corresponding rate of inequality reduction ranges from 1.3% to 1.7% in low-income countries, 0.7% to 1.3% in lower middle-income countries, 1.2% to 1.3% in upper middle-income countries and 0.8% to 1% in high income countries.

However, the estimates of the effects of the initial incidence of EIH on changes in inequality over time for the sub-samples of income groups differ significantly from the full sample in Tables 2 and 3. The initial incidence of EIH is not significant in all specifications for upper middle-income and high-income countries. This includes the interaction of this variable with growth in income per capita. However, for lower middle-income countries, not only does initial EIH incidence have a positive and significant influence (at the 1% level) on changes in inequality over 1990-2019, but initial EIH incidence also interacts with per capita growth to have a negative and significant impact (at the 1% level) on inequality changes. That is, high initial EIH incidence lowers the rate of inequality reduction, but this effect is somewhat counteracted if a country displays higher annual growth in per capita income over 1990-2019.

Regarding income growth, we found no evidence of a relationship between inequality reduction and income growth in advanced countries, but we find two opposing forces in developing countries: income growth as a standalone variable worsens the rate of inequality reduction but when interacted with initial incidence of EIH, rate of inequality reduction improves. For example, a 100% increase in income growth worsens the rate of inequality reduction by 16 % among low-income countries and 21% among lower-middle income countries, at the 5% significant level. And when interacted with initial incidence of EIH, a very small reduction in inequality is observed, at the 1% significant level. Though negligible, this indirect effect of income growth suggests a feedback loop between incidence of EIH and income growth in a manner that improve the rate of inequality reduction. In the case of low-income countries, the initial incidence of EIH only interacts with growth to impact changes in inequality over 1990-2019.

Finally, for both low-income and lower middle-income countries, per capita income growth has a significant and negative impact on changes in inequality over 1990-2019, whereas there is no such significant effect for upper middle-income and high-income countries. That is for the two poorer groups of countries, higher per capita income growth appears to lead to greater reductions in inequality over 1990-2019. In addition, the homogeneity restriction can be rejected for the low and lower middle-income groups but their corresponding β coefficients from the restricted model reported in in column 4 and 8 respectively, in Table 4, is not statistically significant at the 5% level even when we include control variables. As a results, we do not have a statistically significant estimate for the growth elasticity of inequality reduction conditional on initial incidence of EIH. This could be due, in part, to the fact that the effect of the interaction term between growth rate and incidence of EIH is negligible or that the effect of EIH on inequality reduction via income growth may not be straightforward.

Table 4 : The effects of Gini index, incidence of EIH and income growth on changes in inequality, income groups (1990 - 2019)

Variables	Low income				Lower middle income				Upper middle income				High income			
Constant	5.02† [1.652]	3.39** [1.265]	4.97† [1.388]	-0.10 [0.073]	2.50** [0.942]	1.31 [1.268]	-0.73 [1.406]	-0.3** [0.116]	4.62† [1.341]	4.73† [1.246]	5.45† [1.427]	-0.30† [0.104]	3.46† [0.721]	3.14† [0.884]	3.47† [1.210]	0.21** [0.085]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-1.28† [0.414]	-1.55† [0.404]	-1.66† [0.432]		-0.69† [0.240]	-0.91† [0.251]	-1.25† [0.279]		-1.26† [0.343]	-1.25† [0.381]	-1.22† [0.411]		-0.96† [0.202]	-0.94† [0.187]	-0.82† [0.207]	
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.27* [0.132]	0.15 [0.124]			0.21 [0.133]	0.57† [0.143]			-0.02 [0.147]	-0.12 [0.187]			0.03 [0.097]	-0.06 [0.162]	
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.16† [0.048]				0.21** [0.082]				0.03 [0.044]				-0.11 [0.113]	
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.0** [0.000]				-0.00† [0.000]				0.00 [0.000]				0.00 [0.000]	
EIH-adjusted growth rate $\gamma(\mu_{it})(1-\sigma_{it-\tau})$				0.02 [0.035]				0.06 [0.039]				0.08* [0.040]				-0.06 [0.041]
Homogeneity test: Wald test statistics, $\beta_0 + \beta_1 = 0$			10.74†				6.40**				0.39				1.03	
Observations	28	28	28	28	45	45	45	45	49	49	49	49	56	56	56	56
R-squared	0.356	0.433	0.502	0.008	0.099	0.161	0.280	0.034	0.279	0.280	0.308	0.041	0.316	0.317	0.343	0.029

Note: Estimates here are like columns 1 and 2 of Tables 2 and 3 but by income groups. The dependent variable is the annualized change in the log Gini index. The estimates are for 179 countries in total: 56 are high-income countries, 49 upper-middle income countries, 45 Lower-middle income countries and 28 low-income countries for which data on environmentally related deaths and DALYs are available. See appendix Table A4 for list of countries. for which EIH is available. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

As a robustness check, we regroup the low and lower middle-income countries as one sample and both high and upper middle-income countries as a second sample, but the results did not change significantly (see Appendix Table A2). The signs on λ_1 and λ_2 are the same as those reported when the sample was split into the four income groups. Even the coefficient estimates are just few points standard deviation from the average of the coefficient estimate from Table 4. For example, the convergence parameter in Table 4 for the low-income group is -1.28 and that of the lower middle-income group is -0.69 while the coefficient from the combined sample is -0.76 (see Appendix Table A2), approximately 0.23 deviations from the combined mean of -0.99.

5.3 Implications for inequality convergence

Though, higher initial incidence of EIH lowers the rate of inequality reduction, those countries that experience faster reduction in the level of EIH tend to converge in inequality at much faster speed than their counterparts, *all things being equal*. Based on the findings in Tables 2-4, we next ask: At the current rate of annualized rate of inequality reduction in low and lower middle-income countries, how many years will it take these countries to converge to benchmark average inequality of high-income countries which is 35.33 over the period of 1990- 2019? Will the number of years change when we include the effects on annualized inequality reduction of initial incidence of EIH?

To answer both questions, we consider several scenarios but the one reported here uses the predicted values of the annualized rate of inequality reduction from equations (3) and (4) and assumes that, for a selected group of developing countries, their respective initial inequalities are represented by the average over 1990-2019. Table 5 shows the estimated number of years required by each country to converge to some lower inequality index proxied by the average Gini index of 56 high income countries over the entire period of 1990 - 2019. Column 2 shows the average Gini index of each country over the entire period of 1990 – 2019 while column 3 shows the percentage change between the reported EIH in 1990 and that of 2019. Using a compound growth formula and given predicted values of the annualized rate of inequality reduction from equations (3) and (4), average Gini index of each country and the benchmark Gini index of 35.33, we compute the years it will take for each country to converge in the benchmark inequality.

Table 5: Number of years require by selected Lower middle-income countries to converge to benchmark average Gini index of High-income countries (35.34)

Country	Average Gini index, over 1990 – 2019	EIH Reduction between 1990 and 2019 (in Percent)	Years (Based on Equation 3)	Years (Based on Equation 4)
Nigeria	45.3	20.1	91.6	404.0
Senegal	56.3	40.8	120.4	146.8
Mauritania	53.6	45.8	123.7	153.0
Zimbabwe	64.3	23.5	125.1	89.0
Honduras	52.0	35.8	125.7	88.4
Kenya	58.5	17.4	126.2	111.4
Nicaragua	52.5	68.2	130.3	93.1
Tunisia	43.3	20.2	138.2	46.5
Zambia	63.4	41.1	140.2	165.7
Eswatini	64.9	26.6	141.3	115.7
Lesotho	64.2	29.3	141.9	142.0
Cape Verde	60.7	59.6	142.3	114.2
Comoros	63.1	57.2	143.3	172.9
Papua New Guinea	42.8	53.8	143.9	137.5
Angola	60.8	60.9	145.1	262.2
Bhutan	52.1	65.0	150.6	159.9
Pakistan	46.5	14.2	152.5	293.2
Philippines	46.8	22.5	154.5	91.0
Cameroon	57.8	10.4	154.7	191.3
Congo	60.2	38.6	156.0	170.1
Nepal	50.0	62.9	161.4	398.2
Tanzania	53.4	41.3	167.0	301.6
Cote d'Ivoire	58.0	18.4	174.7	233.7
Ghana	55.7	50.4	179.9	274.6
Sri Lanka	47.1	15.5	184.4	66.7
Benin	55.2	9.9	185.9	427.9
Sao Tome and Principe	52.3	66.3	188.0	229.3
Morocco	42.2	39.6	194.3	121.0
India	50.1	38.7	224.0	341.3
Vietnam	37.6	30.8	314.4	38.2

Note: Future projection of number of years (n) are based on the average Gini index of individual countries (g_t) and the average Gini index of 56 High income countries $(\overline{g_T})$ over the entire period of 1990-2019 and the annualized rate of inequality reduction (r). Using the compound growth expression $\overline{g_T} = g_t(1+r)^n$ and solving for n as $n = \left(\ln\overline{g_T} - \ln g_t\right) / \ln(1+|r|)$. r is the predicted values of $\gamma\left(g_{it}\right)$ from equations 3 and 4 respectively. Countries with positive annualized rate of inequality reduction were dropped.

Source: Authors calculation based on data from UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidglobal). Version 31 May 2021.
Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

While it is difficult to explicitly isolate the number of years of convergence attributable to the effect of EIH, we see a trend between the percentage reduction in EIH and the number of years required to converge. On the average, countries with the lowest reduction in EIH require higher than the average number of years to converge to the benchmark inequality (see column 5). For example, Benin which has the lowest percentage reduction in EIH of 9.9 percent happens to require the highest number of years (ie. 427.9) to converge to the benchmark inequality. Despite our optimistic assumptions, many lower-middle income countries may require more than a century to reach the benchmark inequality index of 35.34, despite their strong economic performance, in recent years (see, Johnson and Papageorgiou, 2020).

This simple formulation of cross-country inequality convergence is arguably very optimistic, since some of the countries in this group (such as Cameroon, Nigeria, Congo and others) are flagged as fragile and conflict-affected states by the World Bank and could be subject to geopolitical and economic crises that could derail the convergence process. Moreover, the growth experiences vary among countries within the lower-middle income group, and those countries that are resource and commodity dependent could experience fluctuations that could throw-off our predictions for the better or worse.

It is, therefore, apparent that the large disparities in cross-country inequality cannot easily be surmounted, even under such favorable assumptions regarding convergence. Even within same income group, we observe huge disparities; a fact that that could explain the slow speed of convergence within the groups.

5.4 Robustness Check

To check the robustness of our estimations that uses the Gini index as the measure of inequality, we conducted series of regressions that use indices from Generalized Entropy family including GE (0) or MLD, GE (-1) and GE(1). The main difference between these indices and the Gini index is the part of the distribution they focus on. Unlike the Gini which is less sensitive to the two extremes, the MLD is particularly sensitive to bottom 40 percent of the population, GE (-1) show extreme sensitivity to the very bottom of the income distribution and the Theil, GE (1) is sensitive to the top of the distribution. These differences in the indices shed an important light to the findings of this paper.

We found that inequality indices (ie. MLD or GE (0) and GE (-1)) that placed more emphasis on the bottom of the income distributions are more sensitive to the effects of EIH. The direct effect of incidence of EIH on change in inequality are more profound in GE (-1) models than the Gini index models (compare table 2 or 3 and 6). The associated elasticity is positive and ranges from 0.4 to 0.9 compared to corresponding estimates from that Gini mode which ranges from 0.1 to 0.16. This implies that while 100 percent increase in the incidence of EIH would worsen the change in Gini index by 10 to 16 percent, the change in GE (-1) index worsens by 40 to 90 percent. This result exposes the dangers of EIH in widening the inequality gap between the bottom and top of the income distribution as well as corroborate the narrative that income of the bottom of the global distribution have remain fairly stagnate in recent decades (see Gradín, 2021).

Likewise, the estimated convergence parameters from the GE (-1) models, ranging from 1.1% to 3.2%, are much higher than corresponding estimates obtained in the Gini model (ie. 0.5% to 2%). The GE (1) models have the lowest convergence parameters.

In summary, regressions in Table 6, 7 and 8 consistently corroborate estimates in Table 2 and 3 and point to the evidence of cross-country inequality convergence. As before, the convergence parameter is generally higher when we include incidence of EIH and we found no evidence in support of the hypothesis that incidence of EIH reduces the inequality-reducing impact of income growth in any of the models here.

Table 6: Cross - country convergence in GE (-1) index, incidence of EIH and growth

Variables	1990 – 2010			1990 - 2010			1990 - 2000			2000 - 2019			2000 - 2010		
Constant	5.1†	1.2	0.4	7.2†	4.4†	3.3*	11.7†	8.9†	9.3†	4.0†	-1.6	-1.2	6.0†	0.3	0.9
	[0.698]	[1.288]	[1.540]	[0.993]	[1.472]	[1.887]	[1.836]	[2.624]	[3.007]	[1.162]	[1.691]	[2.058]	[1.934]	[2.326]	[2.714]
Log of GE (-1) index, initial year 1990, $\ln(g_{it-\tau})$	-1.3†	-1.6†	-1.6†	-1.8†	-2.1†	-2.0†	-2.9†	-3.1†	-3.2†						
	[0.185]	[0.215]	[0.210]	[0.256]	[0.296]	[0.290]	[0.486]	[0.543]	[0.562]						
Log of GE (-1) index, initial year 2000, $\ln(g_{it-\tau})$										-1.1†	-1.6†	-1.7†	-1.6†	-2.1†	-2.1†
										[0.307]	[0.340]	[0.338]	[0.482]	[0.563]	[0.558]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.6†	0.6†		0.4**	0.5**		0.4	0.4						
		[0.182]	[0.209]		[0.199]	[0.236]		[0.325]	[0.391]						
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$											0.9†	0.9†		0.9†	0.9**
											[0.251]	[0.307]		[0.347]	[0.435]
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.2			0.2			-0.0			-0.2			-0.1
			[0.140]			[0.166]			[0.142]			[0.165]			[0.248]
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.0			-0.0			0.0						
			[0.000]			[0.000]			[0.000]						
Growth rate interacted with incidence of EIH in 2000, $\gamma(\mu_{it})\sigma_{it-\tau}$												0.0			0.0
												[0.000]			[0.000]
Observations	178	178	178	178	178	178	178	178	178	179	179	179	179	179	179
R-squared	0.253	0.297	0.302	0.303	0.317	0.330	0.281	0.286	0.292	0.079	0.150	0.161	0.081	0.118	0.121

Note: The dependent variable is the annualized change in the log Generalized Entropy family index (GE(-1)). The estimates are for 179 countries for which EIH is available. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † means significant at the 1% level, ** means significant at the 5% level, * means significant at the 10% level.

Table 7: Cross - country convergence in GE (0) index, incidence of EIH and growth

Variable	1990 – 2010			1990 - 2010			1990 - 2000			2000 - 2019			2000 - 2010		
Constant	3.4†	1.9†	1.7**	4.9†	3.5†	3.1†	7.5†	6.2†	6.6†	2.1†	0.4	1.0	3.5†	1.4	2.2*
	[0.432]	[0.586]	[0.683]	[0.558]	[0.699]	[0.858]	[1.007]	[1.273]	[1.421]	[0.641]	[0.749]	[0.871]	[0.975]	[1.035]	[1.235]
Log of GE (0) index, initial year 1990, $\ln(g_{it-\tau})$	-1.0†	-1.3†	-1.2†	-1.4†	-1.6†	-1.6†	-2.1†	-2.3†	-2.3†						
	[0.121]	[0.151]	[0.148]	[0.155]	[0.191]	[0.190]	[0.280]	[0.325]	[0.334]						
Log of GE (0) index, initial year 2000, $\ln(g_{it-\tau})$										-0.7†	-1.0†	-1.1†	-1.1†	-1.5†	-1.7†
										[0.182]	[0.224]	[0.211]	[0.272]	[0.335]	[0.316]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.3†	0.3†		0.3**	0.3**		0.2	0.2						
		[0.089]	[0.101]		[0.102]	[0.120]		[0.161]	[0.185]						
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$											0.3†	0.3†		0.4†	0.4**
											[0.114]	[0.126]		[0.154]	[0.180]
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.1			0.1			-0.0			-0.2*			-0.2
			[0.061]			[0.070]			[0.067]			[0.091]			[0.149]
in Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.0			-0.0			0.0						
			[0.000]			[0.000]			[0.000]						
Growth rate interacted with incidence of EIH in 2000, $\gamma(\mu_{it})\sigma_{it-\tau}$												0.0			0.0
												[0.000]			[0.000]
Observations	178	178	178	178	178	178	178	178	178	179	179	179	179	179	179
R-squared	0.268	0.304	0.307	0.331	0.351	0.359	0.279	0.286	0.291	0.069	0.117	0.142	0.090	0.129	0.153

Note: The dependent variable is the annualized change in the log Mean-log deviation (MLD) or GE(0). The estimates are for 179 countries for which EIH is available. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † means significant at the 1% level, ** means significant at the 5% level, * means significant at the 10% level.

Table 8: Cross - country convergence in GE (1) index, incidence of EIH and growth

Variable	1990 – 2010			1990 - 2010			1990 - 2000			2000 - 2019			2000 - 2010		
Constant	2.8†	1.6†	1.6†	4.0†	2.7†	2.5†	6.5†	5.2†	5.6†	1.4†	0.1	0.9	2.3†	0.6	1.6
	[0.382]	[0.489]	[0.577]	[0.459]	[0.570]	[0.715]	[0.860]	[1.007]	[1.126]	[0.540]	[0.621]	[0.726]	[0.757]	[0.860]	[1.066]
Log of GE (1) index, initial year 1990, $\ln(g_{it-\tau})$	-0.8†	-1.1†	-1.1†	-1.1†	-1.4†	-1.4†	-1.7†	-2.0†	-1.9†						
	[0.104]	[0.137]	[0.136]	[0.125]	[0.163]	[0.164]	[0.230]	[0.284]	[0.286]						
Log of GE (1) index, initial year 2000, $\ln(g_{it-\tau})$										-0.5†	-0.8†	-0.9†	-0.8†	-1.2†	-1.3†
										[0.149]	[0.197]	[0.181]	[0.212]	[0.263]	[0.241]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.2†	0.2**		0.2**	0.3**		0.2*	0.2						
		[0.081]	[0.091]		[0.091]	[0.107]		[0.139]	[0.154]						
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$											0.3†	0.3**		0.4†	0.4**
											[0.103]	[0.105]		[0.128]	[0.138]
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.0			0.0			-0.0			-0.2**			-0.2
			[0.052]			[0.060]			[0.053]			[0.082]			[0.130]
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			0.0			-0.0			0.0						
			[0.000]			[0.000]			[0.000]						
Growth rate interacted with incidence of EIH in 2000, $\gamma(\mu_{it})\sigma_{it-\tau}$												0.0			0.0
												[0.000]			[0.000]
Observations	178	178	178	178	178	178	178	178	178	179	179	179	179	179	179
R-squared	0.255	0.290	0.290	0.314	0.340	0.343	0.286	0.297	0.301	0.056	0.095	0.134	0.067	0.104	0.150

Note: The dependent variable is the annualized change in the log Generalized Entropy family index (GE(1)). The estimates are for 179 countries for which EIH is available. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † means significant at the 1% level, ** means significant at the 5% level, * means significant at the 10% level.

6 Conclusion

The general picture which emerges at the end of this empirical exercise is that incidence of environmentally related impacts on health matter to the story of inequality reduction and convergence. We found strong evidence in support of inequality convergence across-countries and within-income groups. Importantly, we found that though higher initial incidence of EIH simultaneously worsens the rate of inequality reduction, those countries that experience faster reduction in the level of EIH tend to converge in inequality at much faster speed than their counterparts, *all things being equal*. Thus, estimates that exclude EIH may bias the speed of convergence downward.

An influential part of this empirical exercise is the lack of evidence in support of the hypothesis that initial incidence of EIH reduces the inequality reducing impact of income growth. That is because higher rates of income growth, per se, does not promote inequality reduction within countries, instead higher growth rates exist side by side with high inequality, especially in developing countries. This finding is consistent with Ravallion (2014), who found that higher growth rate has not improved inequality within countries, rather the observe falling global inequality is due to falling inequality between countries. Even if inequality does not rise with economic growth, a high level of EIH will mean less average per capita GDP for countries that are disproportionately impacted, mainly developing countries, leading to high inequality within those countries.

Our results hold some important policy implications. Clearly, countries cannot expect to reduce inequality while maintaining high levels of EIH especially in developing countries. If they choose inequality reduction as a priority, then they must implement policy instruments that will cut down the level of EIH and alleviate the conditions of the vulnerable population that are disproportionately impacted. For example, developing countries should build infrastructure and improve access to clean water, proper sanitation and hygiene – which alone account for about 827,000 deaths each year (WHO 2020).

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8 Appendix

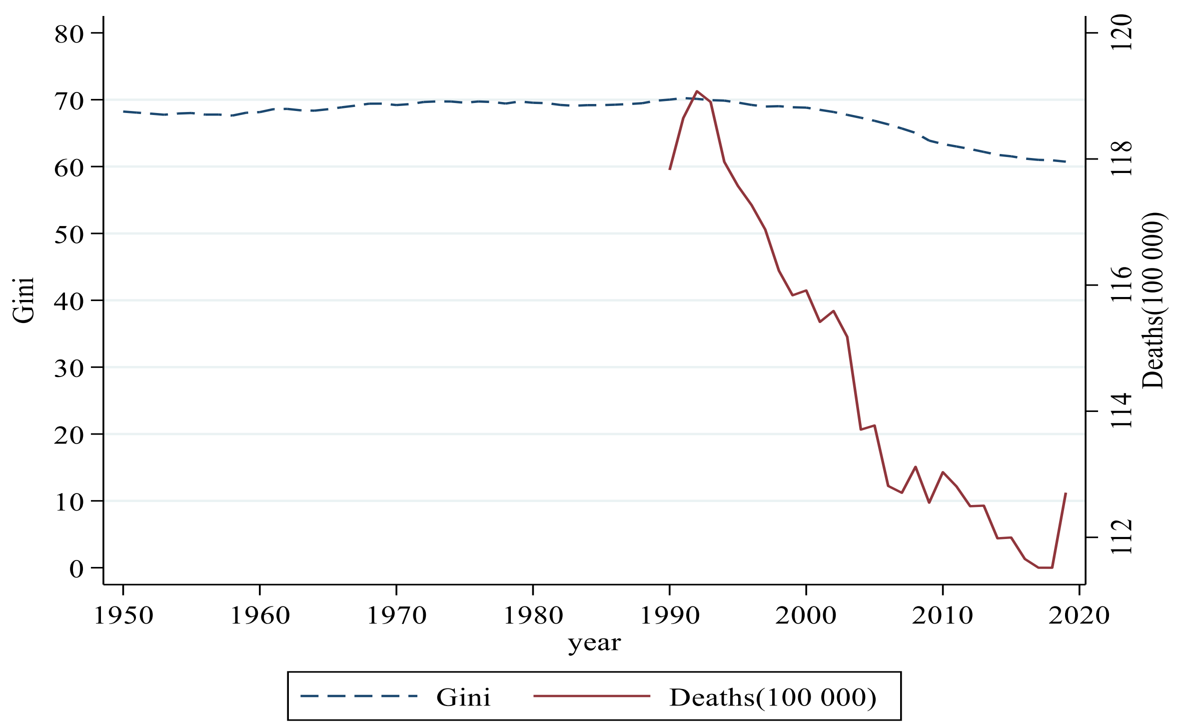

Figure A1: World Gini Coefficient and Environmentally related deaths

Source: Authors calculation based on data from UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidglobal). Version 31 May 2021.
Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

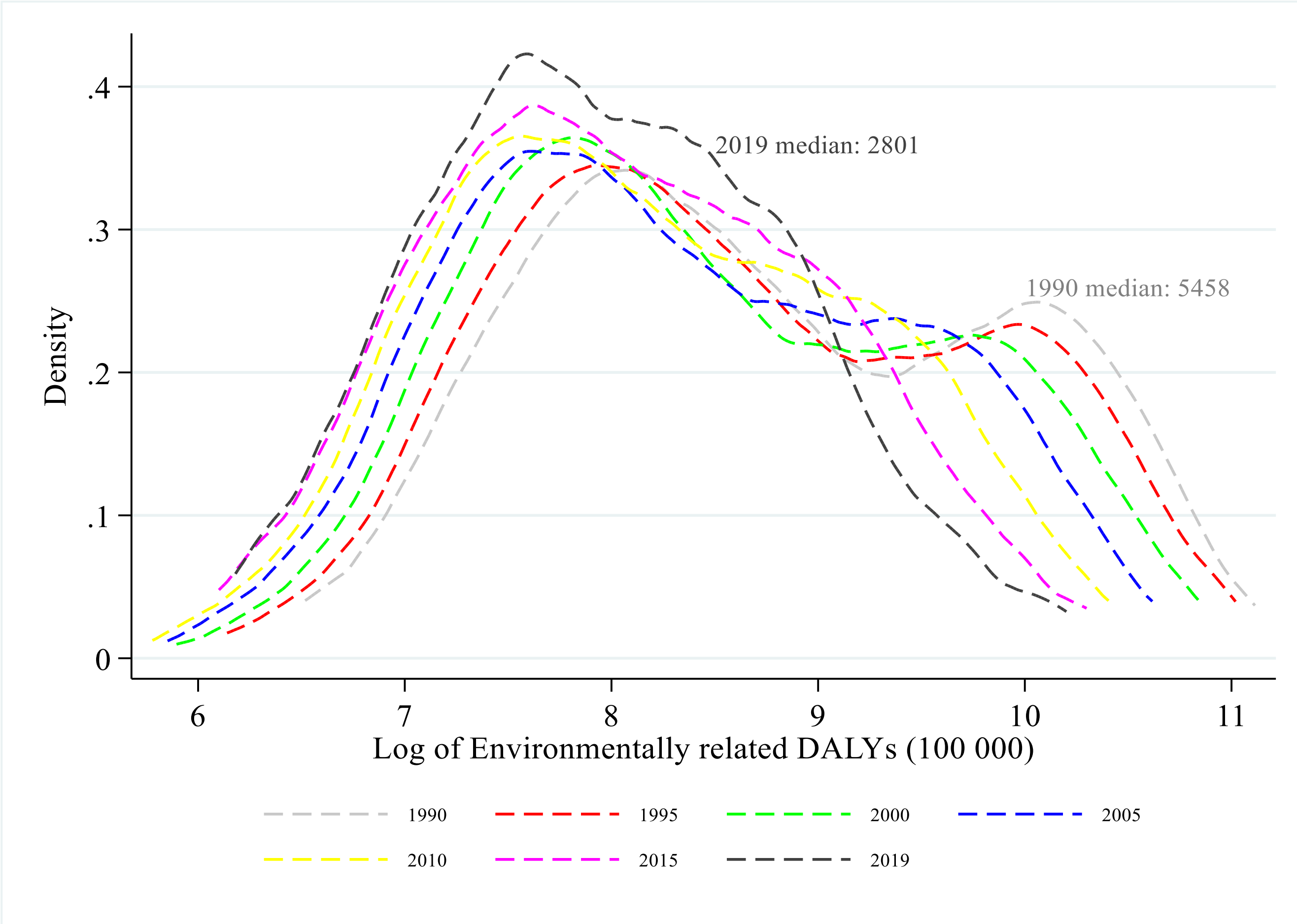

Figure A2: Cross-country Distribution of log Environmentally related DALYs (1990, 2019)
Source: Global Burden of Disease (GBD) dataset, available on the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool)

Table A1: IVE estimates of the effects of initial inequality and incidence of EIH on inequality reduction, 1990-2019

Variable	1990-2019			1990-2010	1990-2000	2000-2019	2000-2010
	Full Sample	Low and lower-middle income	Upper middle and high income	Full Sample	Full Sample	Full Sample	Full Sample
Constant	2.09* [1.249]	-7.33 [5.346]	-10.96 [12.161]	2.45 [2.582]	1.26 [9.349]	2.35 [1.856]	4.04 [3.667]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-4.58† [1.232]	-3.70† [1.382]	-3.24** [1.620]	-8.34** [3.675]	-22.08 [21.257]		
Log of Gini index, initial year 2000, $\ln(g_{it-\tau})$						-5.30† [1.621]	-10.30** [4.879]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$	1.72† [0.545]	2.22** [0.948]	2.82 [2.147]	3.29* [1.684]	9.34 [9.827]		
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$						2.06† [0.652]	4.09** [2.049]
Observations	178	73	105	178	178	179	179

Note: The dependent variable is the annualized change in the log Gini index. The list of instruments for the Gini index include Generalized Entropy family index (GE(-1)) and the income share of the bottom 40%. Both the Durbin (score) and Wu-Hausman statistics have p-values less than 1% level, suggesting that t initial EIH incidence and initial inequality are not exogenous to each other. The estimates are for 179 countries for which EIH is available. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A2: The effects of Gini index, incidence of EIH and income growth on changes in inequality, income groups (1990 - 2019)

Variables	Low and lower-middle income				Upper-middle and high income			
Constant	2.83†	1.71**	0.98	-0.20†	3.75†	3.63†	3.89†	-0.05
	[0.772]	[0.841]	[0.901]	[0.065]	[0.529]	[0.548]	[0.604]	[0.071]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-0.76†	-1.09†	-1.13†		-1.03†	-1.05†	-1.05†	
	[0.195]	[0.209]	[0.202]		[0.142]	[0.174]	[0.175]	
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.25†	0.34†			0.02	-0.01	
		[0.078]	[0.082]			[0.084]	[0.094]	
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.08**				0.01	
			[0.040]				[0.032]	
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.00**				0.00	
			[0.000]				[0.000]	
EIH-adjusted growth rate $\gamma(\mu_{it})(1-\sigma_{it-\tau})$				0.03				0.02
				[0.024]				[0.033]
Homogeneity test: Wald test statistics, $\beta_0+\beta_1=0$			4.20**				0.03	
Observations	73	73	73	73	105	105	105	105
R-squared	0.125	0.228	0.259	0.009	0.324	0.325	0.333	0.002

Note: Estimates here are like columns 1 and 2 of Tables 2 and 3 but by income groups. We regroup countries into two categories; 73 low and lower middle income countries and 105 upper middle income countries. The dependent variable is the annualized change in the log Gini index. See appendix Table A4 for list of countries. Heteroskedasticity-consistent robust standard errors (White) in parentheses. † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.